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Technological catching-up, sales dynamics, and employment growth: evidence from China's manufacturing

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Abstract

This article investigates the microeconomics of employment dynamics, using a Chinese manufacturing firm-level data set over the period 1998–2007. It does so in the light of a scheme of "circular and cumulative causation," whereby firms' heterogeneous productivity gains, sales dynamics and innovation activities ultimately shape the patterns of employment dynamics. Using firm's productivity growth as a proxy for process innovation, our results show that the latter correlates negatively with firm-level employment growth. Conversely, relative productivity levels, as such a general proxy for the broad technological advantages/disadvantages of each firm, do show positive effect on employment growth in the long-run through replicator-type dynamics. Moreover, firm-level demand dynamics play a significant role in driving employment growth, which more than compensate the labor-saving effect due to technological progress. Finally, and somewhat puzzlingly, the direct effects of product innovation and patenting activities on employment growth appear to be negligible.

JEL classification: D22, J01, O33

1. Introduction

For those who believe that the economy is characteristically in a General Equilibrium and Say's law applies, the impact of technical change upon employment is no big deal: *structural unemployment* can only be considered a temporary problem, in that the labor-saving effect of technological progress can be automatically adjusted by the market (see Freeman *et al.*, 1982; Dosi, 1984; Vivarelli, 1995; Vivarelli, 2014 and Calvino and Virgillito, 2017, for discussions and critiques of the implied "compensation theory").

However, the historical evidence militates against any self-equilibrating market mechanism, with long spells of unemployment both in now-developed and developing countries. Indeed, the broad *duality* of technological change implies that the utilization of labor force is endogenously generated by demand creation due to product innovation or expanding existing markets, on the one hand, and continuous labor displacement due to process innovation, on the other hand. In that, the homeostasis between the two forces cannot be guaranteed, because of the major discontinuities in technological innovation, the long-term changes in the balance process vs. product innovation, the "stickiness" of consumption baskets, and the long-term fluctuations in the rates of innovation themselves (more on this in Dosi, 1982, 1984).

If this is the case, however, it becomes crucial to understand the determinants of employment dynamics also at sectoral and firm levels. This is what we shall do in the following, examining the impact of technological catching-up, sales dynamics, and innovation activities on employment growth in China, making use of a large representative sample of Chinese manufacturing firms covering the period of Chinese economic boom before the global financial crisis. Our approach to the relationship between technological change and employment dynamics is a *partial disequilibrium* one, grounded on heterogenous patterns of firm-level learning and catching-up, fueled by Kaldorian processes of "circular causation"—that is of dynamic increasing returns—, linking productivity, sales growth, and further efficiency gains (Freeman, Clark, and Soete, 1982; Dosi, 1984; Dosi, Pavitt, and Soete, 1990; Freeman and Soete, 1994; Vivarelli and Pianta, 2000; Lee, 2013; Dosi, Grazzi, *et al.*, 2015; Bogliacino *et al.*, 2017). In turn, sales dynamics, at least in the case of China, have been driven to a good extent by export growth. We interpret the latter in a "technology-gap" perspective, whereby the absolute advantages/disadvantages of sectors and firms evolve according to (i) the dynamics of the technology they master compared to their foreign competitors, (ii) their cost competitiveness (i.e. relative unit labor cost, RULC), and (iii) the elasticity of their sales to world income dynamics. Exports, as such an important indicator for country's international competitiveness, but also play an important role in stimulating macroeconomic activities and employment growth through the "foreign-trade multiplier" (Thirlwall, 1979, 1980; MacCombie and Thirlwall, 1994).[1] Of course the overall dynamic is affected by the sectoral ones which in turn sums up the dynamics of a large number of highly heterogenous firms.

Hence, in the following we start by studying the sectoral-level employment dynamics as the outcome of sectoral average productivity growth and sales growth. In turn, exports are an important component of sales, and they are jointly affected by world income growth, variations on sectoral unit labor cost (relative to the "rest of the world"), and (relative) innovativeness.

Behind sectoral dynamics, however, rest a multiplicity of heterogenous firm-level patterns. Thus, next, we investigate the *microeconomics* of employment as the outcome of firm-specific technological learning, capital accumulation, and sales variation within narrowly defined sectors. The question is the extent to which firm-level employment dynamics is affected by the labor displacement associated with productivity growth as compared to the labor creation induced by product innovation and sales growth. Furthermore, we address the two-sided impact of sales growth on employment growth: firm-level demand expansion creates, other things being equal, job opportunities, but it also plays a significant role in driving up productivity due to Kaldorian increasing returns and capability accumulation (Cimoli, Dosi, and Stiglitz, 2009).

In brief, we find that Chinese employment dynamics reveals a *Keynesian–Kaldorian adjustment* story, in presence of a fast and very successful *technological catching-up*. At the sectoral level, labor demand is largely driven by sectoral sales growth, while the growth of productivity is markedly labor displacing, even if it helps cost competitiveness (proxied by RULC). In turn, sectoral sales growth is primarily determined (via exports) by world income growth and to a less extent by the variations of sectoral unit labor cost. Interestingly, during the period under investigation, proxies for product innovativeness do not seem to contribute directly to sales/or export growth, except few sectors (probably a sign that sectors as a whole have not reached the international technological frontier). At the firm level, the labor-displacing effects of productivity growth are often overcompensated by the dramatic growth in sales. Together, productivity levels do show positive effect on employment growth through the replicator-type dynamics: more productive firms grow more in terms of employees. Finally, at micro level, product innovation does appear to have positive effect on labor demand. Conversely, firms' patenting activities (in the United States) do not correlate with employment growth (note however that the surge in Chinese patenting abroad is a quite recent phenomenon).

The article is organized as follows. Section 2 briefly discusses the state of the art on the evidence both at the sectoral and firm level. Section 3 presents our simple interpretative models. Section 4 describes the data. Section 5 presents the broad patterns of growth, export, and employment dynamics in China up to the Crisis. Section 6 presents our sectoral- and firm-level empirical results. Section 7 concludes.

1 Kaldor (1970) and Thirlwall (1979) suggest that "if balance of payments equilibrium must be maintained, a country's long-run growth rate will be determined by the ratio of its rate of growth of exports to its income elasticity of demand for imports" (Thirlwall's law). As known, China overshot the constraint and ran throughout a significant surplus.

2. Employment dynamics at sectoral and firm level: a brief review of the evidence

The empirical literature on the relationship between technical change and employment at both sectoral and firm level is critically reviewed in Calvino and Virgillito (2017) to which we refer for all details and the full list of references. Here let us just mention the thrust of the findings.

In general the literature—both theoretical and empirical—on sectoral-level employment dynamics is based on *partial disequilibrium framework* interpreting it as a result of structural change involving both embodied and disembodied technological change and changing patterns of consumption (for a seminal theoretical model, see Pasinetti, 1981). On the empirical side one often finds an overall positive relationship between structural change, proxied by relative sectoral value-added growth and growth in employment; a negative relationship between productivity growth and employment growth; and a positive effect of product innovations on sectoral employment growth.[2]

A second stream of literature adopts the Haltiwanger-type job flow measure (Davis and Haltiwanger, 1990; Davis *et al.*, 1998) and finds that sectors with more process innovation have a higher job destruction rate and a lower net employment growth rate, vice versa for sectors with more product innovation.[3]

Notice that most of the foregoing studies refer to developed countries. An interesting question is whether the differential impact of product vs. process innovation applies also to the sectors on a catching-up country, like China. We shall address that in the following.

Finally, a third stream of studies which is not generally associated with the analyses of sectoral dynamics is based on a technology-gap trade framework and emphasizes in the first instance the *intercountry* differences in innovativeness (within the same sector) as the basis of international trade flows and implicitly sectoral dynamics. Rather than interindustry variations in the technological "endowments" of a specific country, it is the variation in innovativeness within each sector across countries which is deemed to be crucial. Indeed, in Dosi *et al.* (1990) and Dosi, Moschella *et al.* (2015), one suggests that countries' sectoral market shares are mainly shaped by technological factors, while cost advantages/disadvantages do not seem to play any significant role. However, the technology-gap framework has never been extended to the studies on employment dynamics. This is another task that we shall undertake in the following.

Considering firm-level employment dynamics, let us refer again Calvino and Virgillito (2017). Only some remarks are in order. Notice, first, that a much wider literature addresses the issue, but also that the methodologies are quite different mostly employing to different degrees some *equilibrium* assumptions concerning micro decisions on the demand for labor together with in our view equally questionable assumptions on the existence of some well-behaved production function.[4] This notwithstanding, some relatively robust patterns have emerged.

A large number of micro-econometric studies detect the direct impact of innovation on employment, without identifying the compensation mechanism (the indirect effect) through lowering cost competitiveness and creating/enlarging markets.[5]

A number of empirical works have tried to disentangle the effect of process and product innovation on firm-level employment. Most studies have found a positive impact of product innovation on employment via new demand, especially when the new products cannot perfectly substitute the old products within the same firm, while the impact of process innovation seems more ambiguous. The direct impact of process innovation is to increase productivity, implying a labor-displacement effect.[6] However, there can be an indirect effect of process innovation on employment that the increasing productivity may be associated with sales growth and employment growth driven by strengthening cost competitiveness.

There have been few empirical studies on the employment impact of innovation or technological catching-up in the context of developing countries.[7]

2 See among others Pianta *et al.* (1996), Vivarelli *et al.* (1995), Pianta (2000), Bogliacino and Pianta (2010), Mastrostefano and Pianta (2009), and Bogliacino and Vivarelli (2012).

3 See among others Greenan and Guellec (2000) and Meriküll (2010).

4 The roots of our skepticism are discussed in Dosi and Grazzi (2006), Dosi and Nelson (2010), and Dosi *et al.* (2016).

5 See among others Van Reenen (1997), Greenhalgh *et al.* (2001), Piva and Vivarelli (2005), Coad and Rao (2011), Bogliacino *et al.* (2012), Ciriaci *et al.* (2015), and Van Roy *et al.* (2015).

6 See among others Greenan and Guellec (2000), Hall *et al.* (2008), Harrison *et al.* (2014), Evangelista and Vezzani (2012), Herstad and Sandven (2015), Zimmermann (2009), and Triguero *et al.* (2014).

7 Exceptions are Benavente and Lauterbach (2008) and of course Crespi *et al.* (2018, forthcoming) and Huang *et al.* (2018, forthcoming) in this issue

Note that the foregoing results stem implicitly or explicitly from an equilibrium framework whereby labor demand is derived from an underlying "production function." What does one see when one abandons such a perspective and considers the evidence of microeconomic employment dynamics in a (micro-founded) disequilibrium framework? This is one of the questions that we shall address in the following.

3. Interpretative models

3.1 Sectoral-level employment dynamics: the model

Let us consider sectoral employment change starting from the simple *identity*:

$$N_{jt} \equiv \frac{Y_{jt}}{\Pi_{jt,}} \tag{1}$$

where N_{jt} is sectoral employment (sector j at time t), Y_{jt} is sectoral output,[8] and Π_{jt} is sectoral (weighted-) average labor productivity. The dynamic version of (1) is:

$$\frac{\Delta N_{jt}}{N_{jt}} = \frac{\Delta Y_{jt}}{Y_{jt}} - \frac{\Delta \Pi_{jt}}{\Pi_{jt,}} \tag{2}$$

where ΔN_{jt} is $N_{jt} - N_{j,t-1}$. Here, obviously, sectoral employment dynamics is positively associated with sectoral-level output/demand growth which, in turn, we shall argue on the interpretative side, is shaped by the sector's absolute competitiveness in the international market, and negatively associated with sectoral labor productivity growth. Notice that, labor productivity, as measured in actual data, does not capture only physical productivity but also reflects variations in value added generated, for example, by high-quality products which are sold at higher prices. More generally, productivity is related to the way in which the process of production is carried on (on average) in the sector, and thus also reflects the efficiency of organizational routines and the dynamic capabilities of the firms in that sector and country.

Next, let us derive the determinants of the dynamics of sectoral absolute competitiveness as a function of the dynamics of technological absolute advantage, cost advantages, and world income growth. In a first approximation suppose that the variation of demand of sector j of a country, say China, depends on the change of the commodities' relative prices in sector j of the country to the world price of the same sector (P^*_{jt}) and the variation of world income (Y_{wt}).

$$\frac{\Delta Y_{jt}}{Y_{jt}} = \eta_p \frac{\Delta P^*_{jt}}{P^*_{jt}} + \eta_y \frac{\Delta Y_{wt}}{Y_{wt,}} \tag{3}$$

where η_p is the price elasticity of demand (plausibly $\eta_p < 0$) (i.e., an increase in price leads to some proportional decrease of demand), η_Y is the income elasticity of demand ($\eta_Y > 0$) (i.e., the degree to which increases in world income lead to proportional increases of demand).

The relative price of commodities of sector j is a function of sectoral RULC. The variation of the relative price in sector j is:

$$\frac{\Delta P^*_{jt}}{P^*_{jt}} = \mu_1 + \frac{\Delta RULC_{jt}}{RULC_{jt}}, \tag{4}$$

where μ_1 is a constant capturing the dynamics of the markup, RULC is the relative (Chinese) ULC of sector j to the world ULC of the same sector.[9] The RULC can be expressed as $\frac{ULC_{China,jt} \times E_t}{ULC_{World,jt}}$ where E_t is the trade-weighted bilateral exchange rate index, and the dynamic version of relative ULC can be expressed as $\frac{\Delta ULC_{China,jt}}{ULC_{China,jt}} + \frac{\Delta E_t}{E_t} - \frac{\Delta ULC_{World,jt}}{ULC_{World,jt}}$.

8 Here, we assume for simplicity, sectoral output equals demand.

9 Notice that the unit labor cost of sector j in country i (ULC_{jt}) is defined as the ratio between sectoral average wage per employee (W_{jt}) and sectoral labor productivity (Π_{jt}).

In comparison with the "world," the dynamics of sectoral *cost advantages/disadvantages* captures the joint effect of wages and labor productivity.

We can plug the price variation Equation (4) into the demand growth Equation (3). Thus:

$$\frac{\Delta Y_{jt}}{Y_{jt}} = \mu_2 + \eta_p \frac{\Delta RULC_{jt}}{RULC_{jt}} + \eta_y \frac{\Delta Y_{wt}}{Y_{wt}}, \tag{5}$$

sales growth of sector j is a function of the growth of RULC of China and world income growth. Indeed, Equation (5) just states that sectoral sales growth is jointly determined by some cost effect and some world income effect. Sectoral sales growth is the outcome of an *absolute measure of competitiveness* (i.e. *independent of the competitiveness of other sectors within China*). The cost effect is measured by (the variation of) RULC, as a proxy of *cost advantages*, which is jointly determined by (the dynamics in) wage gap (measured in international currency) and the dynamics in labor productivity gaps, which, it is important to note, reflect underlying technological catching-up dynamics.

Finally, we augment the estimates with a patent-based variable, a measure of sectoral *technological absolute advantages*, as compared to sectors/countries "on the frontier," specially in product innovations. Thus:

$$\frac{\Delta Y_{jt}}{Y_{jt}} = \alpha + \eta_p \frac{\Delta RULC_{jt}}{RULC_{jt}} + \eta_y \frac{\Delta Y_{wt}}{Y_{wt}} + \beta \frac{\Delta PATS_{jt}}{PATS_{jt}}, \tag{6}$$

where $PATS_{jt}$ proxies the sectoral "frontier" innovativeness. In this work, the proxy is Chinese patents in the United States Patent and Trademark Office (USPTO).

After estimating Equation (6) and evaluating its robustness, we shall use it to estimate the overall sectoral employment effect of export dynamics.

3.2 Micro-foundation of technology-gap theory and employment dynamics: a general disequilibrium firm-level model

In line with theoretical interpretation of the sectoral-level employment growth, our firm-level employment dynamics is jointly shaped by the overall market growth, the firm-specific labor productivity, and the dynamics of firm-specific competitiveness (influencing firm's sales growth) within a narrowly defined (four-digit) sector. Let us start from the simple relation:

$$\frac{\Delta N_{ijt}}{N_{ijt}} = g\left(\frac{\Delta \Pi_{ijt}}{\Pi_{ijt}}, \frac{\Delta Y_{ijt}}{Y_{ijt}}\right), \tag{7}$$

where $\Delta N_{ijt}/N_{ijt}$ denotes the employment growth of firm i in sector j and year t; $\Delta \Pi_{ijt}/\Pi_{ijt}$ is firm's labor productivity growth; and $\Delta Y_{ijt}/Y_{ijt}$ stands for the growth of sales of the firm.[10]

Of course, the growth of sales of a firm depends on the growth of the market $\Delta Y_j/Y_j$ and the dynamics of the share in it of i, $\Delta S_{ij}/S_{ij}$. The latter, we suggest in an evolutionary perspective, depend on firm-specific *competitiveness*. The notion is grounded on the persistent heterogeneity among firms and the systematic processes of competitive selection among them. Firms persistently differ over all dimensions one is able to detect. Idiosyncratic capabilities and, dynamically, idiosyncratic patterns of learning by individual firms are the general rule. In turn, such persistently heterogeneous firms are nested in competitive environments which shape their individual economic performances and collectively the evolution of the forms of industrial organization. Differences in product characteristics and in the processes of production are central features of the competitive process by which some firms grow, some decline, and some go out of business.

Evolutionary approaches have often modeled the competitive process by different instantiations of some *replicator dynamics*. The bottom line is a relation between some corporate features—that is, technological, organizational, or behavioral traits—which the particular interactive environment "favors," on the one hand, and the dynamic

10 Of course, for each firm the relation (7) is an identity, but overall it captures the *average* effect of productivity and sales growth upon employment growth and that stops being an identity.

performance in the *carriers* of such characters in the relevant population on the other hand (see, among others, Silverberg *et al*. (1988); Dosi *et al*. (1995), and the discussion in Dosi and Nelson (2010)). In its linear specification:

$$\frac{\Delta S_{ijt}}{S_{ijt}} = f(E_{ijt} - \bar{E}_{jt})S_{ij,t-1}, \tag{8}$$

where $\Delta S_{ijt}/S_{ijt}$ is the rate of change in the share of firm i in the total production of the sector; E_{ijt} represents firm's competitiveness (capturing the firm's technological and cost advantages); and $\bar{E}_{jt}$ is the average of the variable(s) over all firms within the sectors.

Below we shall proxy competitiveness with the productivity levels of firm i (Π_{ij}) relative to the sectoral average, and, in some specifications, with the shares of new products in the total output of the firm.

In the opposite direction, in the spirit of the circular and cumulative causation scheme, increasing returns in the accumulation of capabilities imply a positive association with demand dynamics, that is the dynamic version of Kaldor–Verdoorn law:

$$\frac{\Delta \Pi_{ijt}}{\Pi_{ijt}} = h\left(\frac{\Delta Y_{ijt}}{Y_{ijt}}\right). \tag{9}$$

Hence, the micro-founded "technology-gap" theory of employment growth, based on the interaction between growth in productivity and demand variation, develops along three different sequences. First, increases in labor productivity are likely to lead to labor shedding, other things being equal. However, second, relative labor productivities affect the competitiveness of each firm and through that the dynamics of market shares and thus its demand. Finally, third, increases in productivity are stimulated by growth in production through increasing returns, learning, and the accumulation of capabilities.

4. Data and descriptive statistics

4.1 Database description: firm-level data

This work draws upon firm-level data from the Annual Survey of Industrial Enterprise collected by the Chinese National Bureau of Statistics (NBS). The data set includes all industrial firms with sales above 5 million RMB covering period 1998–2007 and has already been employed in other empirical investigations, including Dong and Xu (2009), Yu *et al*. (2015), and Yu *et al*. (2017).[11] The surveys cover approximately 55–79 million workers, accounting for about 7.5%–10.5% of the total employment. Each firm is assigned to a sector according to the four-digit Chinese industry Classification (CIC) system that closely matches the Standard Industrial Classification (SIC) employed by the US Bureau of Census.[12] Out of the comprehensive set of all firms, we focus on manufacturing firms only (CIC 13—42). Table A1 (in Appendix A) shows the summary statistics of manufacturing firms. The total number of employees in the manufacturing sector has increased from 50 in 1998 to 68 million in 2007. (In fact, it decreased by 5.7 million during period 1998 and 2001, then increased thereafter.)[13]

4.2 Variables used in firm-level analysis

We measure the firm-level employment growth rate as the log difference of employment levels of 2 consecutive years: $\Delta n_{ijt} = n_{ijt} - n_{ij,t-1}$, where n_{ijt} is $\ln(N_{ijt})$. Productivity (π_{ijt}) is the (log) ratio of value added (at constant prices) over the number of employees. Productivity growth ($\Delta \pi_{ijt}$) is the log difference of productivity levels of 2 consecutive

11 Industry is defined to include mining, manufacturing, and public utilities, according to NBS of China. Five million RMB is approximately $US 600,000.

12 In 2003, the classification system was revised. Some sectors were further disaggregated, while others were merged together. To make the industry code comparable over time, we adopted the harmonized classification proposed in Brandt *et al*. (2012).

13 We have applied a few cleaning procedures to the data set to eliminate visible recording errors. We dropped firms with missing, zero or negative output, value-added, sales, original value of fixed assets, employment (<8). And we keep firms existing for at least 2 consecutive years.

Table 1. Summary statistics (mean) on the firm-level data set (after cleaning)

Year	Number of firms	Employment	Sales	Labor productivity	Employment growth	Sales growth	Labor productivity growth	Ratio of new product in output	2-year MA investment intensity
1998	10,8286	379	43,847	44	NA	NA	NA	0.029	NA
1999	12,5917	348	45,266	48	−0.038	0.016	0.070	0.028	NA
2000	12,6054	337	53,875	54	−0.022	0.049	0.061	0.029	0.291
2001	13,8410	307	55,577	59	−0.024	0.007	0.046	0.031	0.269
2002	14,9189	292	60,690	68	−0.001	0.071	0.083	0.028	0.266
2003	16,2086	285	73,925	76	0.018	0.129	0.099	0.027	0.253
2004	21,1534	235	73,162	88	0.013	0.118	0.047	0.034	0.242
2005	23,8160	242	87,461	97	0.051	0.189	0.154	0.036	0.236
2006	26,5912	233	98,964	114	0.024	0.178	0.171	0.039	0.229
2007	24,8299	245	12,8191	137	0.032	0.199	0.177	0.038	0.205

Note: Sales are in current price; labor productivities are in 1998 constant price; unit 1000 RMB. Growth rates are calculated as log differences of real value, at 1998 constant price.

years.[14] Productivity levels and growth can be considered proxies for process efficiency and process innovation, admittedly defined in a very broad sense, and with some important caveats. Productivity *as measured* could also represent product innovations, especially if we consider revenue productivity, and in some sense, we partly capture revenue productivity. Industry deflators do not cancel completely the price effects in productivity.

We define firm’s sales growth (Δg_{ijt}) as the log difference of (constant price) sales in 2 consecutive years. We use 2-year moving average of investment intensity as proxy for investment: $I_{ijt} = \frac{INV_{ijt}+INV_{ij,t-1}}{VA_{ijt}+VA_{ij,t-1}}$, where INV_{ijt} is real investment, and VA_{ijt} denotes real value added.[15] We use the percentage share of new products in total output as our proxy for product innovation (NEWPROD).[16] Note that, only less than 5% firms display positive shares of new products. Firm age is computed using information on firm’s foundation year. Our proxies for firm size are (log-) number of employees and (log-) sales. Table 1 provides basic descriptive statistics of the main variables used in the empirical analysis. Finally, we use as yet another proxy for innovativeness the patents granted in the United States identified through a procedure discusses in Appendix B.[17]

4.3 Sectoral data

For sectoral analysis, our firm-level data set has been aggregated at four-digit sectoral level, to obtain total (real) value-added, total employment, total (real) sales, and total (real) exports for each four-digit sector. Sectoral employment growth, sales growth, and labor productivity growth are calculated as above. Table A2 (in Appendix A) provides basic descriptive statistics of the main variables used in the empirical analysis. The growth rate of RULC of sector j at time t can be derived based on: (i) the growth rate of Chinese unit labor cost of sector j at time t; (ii) the growth of trade-weighted bilateral exchange rate index (i.e. trade-weighted “world currency” per Chinese yuan);[18]

14 Sales, value-added, and output are all deflated using the same deflator constructed by Brandt *et al.* (2012).

15 Notice that, we compute real investment at time t as the difference of firm’s real capital stock between time t and t–1. The time series of real capital stock are computed following Brandt *et al.* (2012) that apply a standard perpetual inventory method, with a 9% rate of depreciation.

16 According to NBS of China, “new products” are defined as product adopting new technology and/or new design, or products that have been significantly improved in performances and functions over existing ones by improving their structure, materials, and/or process technics. Hence, these “new products” are new to the enterprises but not new to the market. Because output of new product is not available for years 2001 and 2004, we fill in the gaps using the averages between the values of previous year and the next year for each firm.

17 A dummy variable distinguishes firms holding patent for at least 1 year in the USPTO during 1998-2007.

18 To calculate it, we use two variables (i) G7 trade weights, calculated by authors based on NBSC statistical yearbook; (ii) bilateral exchange rates between Chinese yuan and G7 currencies, directly available from IMF.

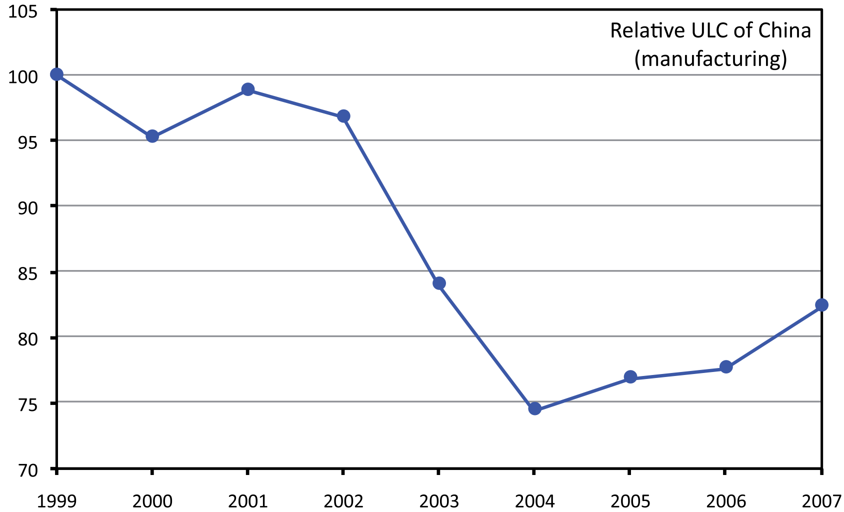

Figure 1. Unit labor cost of Chinese manufacturing relative to the world (proxied by G7 countries).

Source: Chinese firm-level data set (Chinese unit labor cost); OECD.stat (G7 unit labor cost); China Statistical Yearbook (China-G7 trade weights); IMF (exchange rates between China and G7 countries).

and (c) growth of world unit labor cost.[19] We proxy world income growth using growth rate of world gross domestic product.[20] We use the share of Chinese patents in total foreign patents granted in the United States for sector *j* year *t* as a proxy for sectoral innovativeness (source: PATSTAT Version 2014a, USPTO patents only. For details, see Appendix B).[21]

5. The general picture

There are five fundamental characteristics of China's "economic miracle" which place the discussion that follow in the proper context.

First, Chinese economic growth has occurred and is occurring in *dual* economic system, characterized by the persistent coexistence of a relatively "modern" sector and a "traditional rural" one. The *unlimited supplies of labor* from the traditional sector served as a source of cheap labor for almost three decades of rapid capital accumulation and industrialization in China, without dramatic increase in wages (see Lewis, 1954; Lutz, 1958; Cai and Wang, 2010). This is also reflected in the limited role of wages in the growth of Chinese aggregate demand during the early phase of transition, and in a rather stable import propensity. Indeed, Chinese manufacturing RULC shows a *decreasing* trend until 2004 and kept stable/or mildly increased afterward (see Figure 1), suggesting an increasing *cost advantage*, too, until 2004.

Second, the dramatic productivity growth and catching-up has been well documented. For example, Yu *et al.* (2015) estimate a 10% labor productivity growth and Brandt *et al.* (2012), a 7.7% TFP growth, intimately coupled with process of technological and organizational learning and knowledge accumulation (see Fu an Gong, 2011; Yu *et al.*, 2017).

Third, export grew at a spectacular rate even if the export share into the total Chinese manufacturing output has increased only mildly from 18.3% in 1998 to 22% in 2006 (see Table A1). The foreign-trade multiplier played an important role during the Chinese catching-up process, with export fueling effective demand and leading to overall increase in output and employment (see Lin and Li, 2003; Fu and Balasubramanyam, 2005).

19 We proxy it using the G7 countries' manufacturing ULC growth rates: source OECD.stat.
20 Source: IMF World Economic Outlook Database, gross domestic product, constant prices, percentage change.
21 The United States as a major technology "market" indeed appears to be a good mirror of the Organisation for Economic Co-operation and Development (OECD) or world technology market: more in Dosi *et al.* (1990).

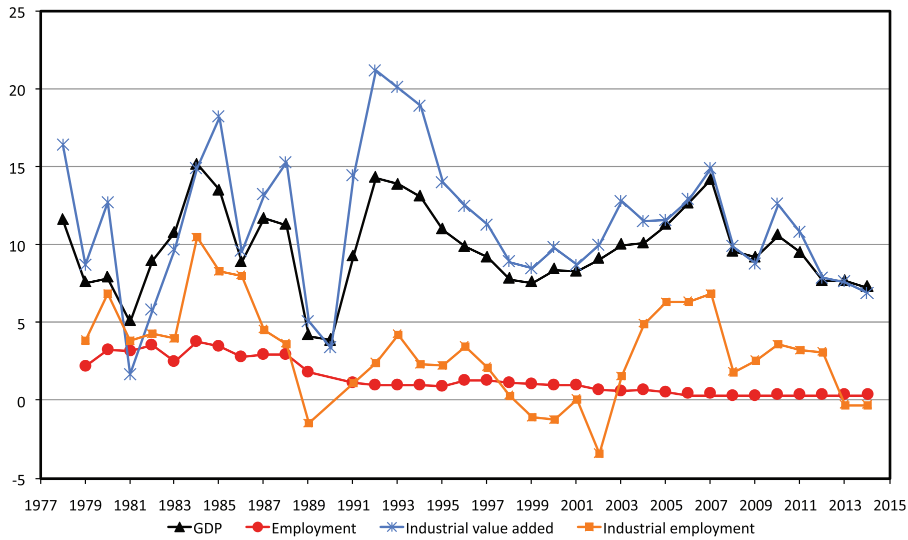

Figure 2. Growth rates of gross domestic product (GDP), industrial value added, total employment, and industrial employment.

Note: The employment growth rate time series are discontinuous in 1990, as the employment statistics before 1990 are from a different data collection method.

Source: National Bureau of Statistics of China.

Fourth, the employment growth has been much lower than the overall income growth of China. This is hold both for the economy as a whole and for the industrial sector alone, as shown in Figure 2.[22]

The elasticity of employment to output, measured as ratio between the rate of growth of employment and the rate of growth of production (cf. Figure 3), shows a steady decreasing trend from 0.15 in 1998 to 0.04 in 2010, with a high volatility in the industrial sector. Such an elasticity was even negative between 1998 and 2003, due to the massive layoff of employees in the state-owned enterprises coupled with the "ownership transformation" process.[23] It surged to around 0.5 during 2004–2007, dropped again significantly to 0.2 in 2008, the year of the global financial crisis. Both in the overall economy and in the industrial sector, (almost) *jobless growth* appears to have precociously emerged as a dominant characteristic.

Fifth, "on the frontier" innovative activities are a quite recent phenomenon in China. Table 2 shows the patenting activities in the USPTO. The number of Chinese patents granted has increased from 151 to 4527, accounting for 0.17% in 1998 and 2.46% in 2007 of the non-US assignees's patents (i.e. the year refers to the filing year of the granted patents). Indeed, patenting has exploded since then.

6. Empirical results

6.1 Sectoral-level empirical estimates

First, we estimate Equation (2) for each two-digit sector, that is sectoral-level employment dynamics as the joint outcome of productivity growth and sales growth. Results are shown in Table 3. Productivity growth displays very significant negative association with employment growth at the sectoral level, while sectoral sales growth contributes significantly to employment growth.[24]

22 Industry is composed by mining, manufacturing, construction, and utilities.

23 For the labor restructuring process associated with the ownership transformation in China, see Dong and Xu (2009) and Yu *et al.* (2015).

24 In the next few paragraphs, we discuss some inter-industry differences. However, admittedly, we do not consider possible inter-sectoral interdependences in demands and productivities via input/output flows.

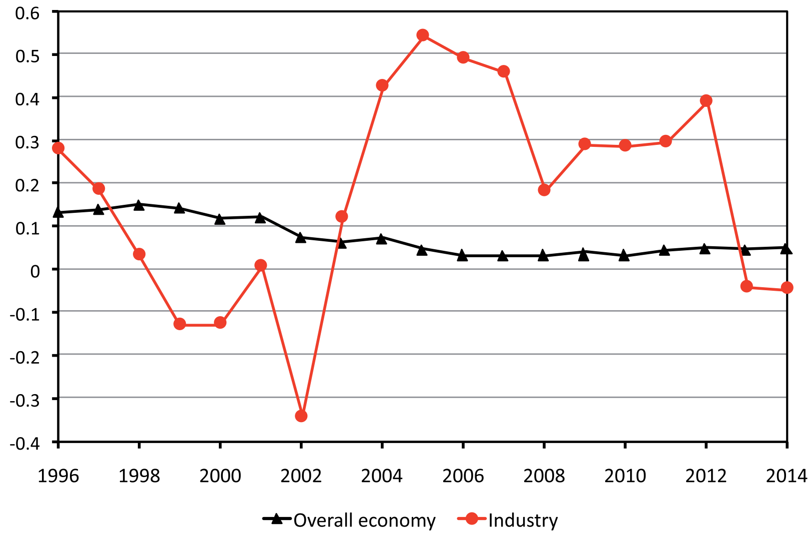

Figure 3. The elasticity of employment growth to GDP growth and industrial value-added growth.

Source: National Bureau of Statistics of China.

Table 2. Summary statistics of the patenting activities in the USPTO

Year	Number of Chinese patents	% of Chinese patents in non-US patents	% of Chinese patents in world patents
1998	151	0.17	0.08
1999	226	0.23	0.11
2000	345	0.31	0.15
2001	579	0.39	0.19
2002	821	0.54	0.26
2003	1130	0.68	0.35
2004	2091	1.11	0.57
2005	2880	1.40	0.72
2006	3963	2.11	1.01
2007	4527	2.46	1.15

Note: If one patent corresponds to multiple assignee persons (possibly from multiple countries), we assign equal weights to each of the assignee persons.

Source: PATSTAT (version 2014a). Year refers to patent application year.

Adopting the same model, we estimate the association between *export growth* and employment dynamics. Results are shown in Table 4. The strong positive association of export growth on employment growth appears in the majority of sectors, and in particular, in the manufacturing of furnitures, chemical and metal products, communication equipment and computers, and measuring instruments. The significant labor-displacing effect of productivity growth is particularly revealed in textile, wood products, furnitures, paper, and plastics.

Second, we estimate Equation (5), that is sectoral sales growth as the joint outcome of the variation of Chinese RULC and world income growth. The estimates are shown in Table 5.[25] The effect of income elasticities dominates

25 Here, we adopt "regression through the origin (RTO)": it implies that the dependent variable is assumed to be 0 when independent variables are 0s. In our case, it means that we assume that when the growth rates of RULC and world income are nil, the growth of Chinese sectoral sales/export is equally nil. In fact, the assumption stands for a time zero

Table 3. Sectoral-level employment dynamics (ΔN_{jt}) Equation (2)—sales growth

CIC	Sector	$\Delta\Pi_{jt}$	ΔY_{jt}	Constant	# Obs.	R^2
	All manufacturing	−0.4803***	0.7743***	−0.0031	3812	0.7475
		(0.0255)	(0.0219)	(0.0098)		
13	Food from agriculture products	−0.4819***	0.8164***	0.0099	135	0.8272
		(0.0515)	(0.0634)	(0.0258)		
14	Food	−0.5414***	0.8692***	0.0036	171	0.8460
		(0.1319)	(0.0605)	(0.0269)		
15	Beverages	−0.5135***	0.6470***	0.0418*	108	0.7605
		(0.0742)	(0.0606)	(0.0186)		
16	Tobacco	−0.4539***	0.3500*	0.0379	27	0.6967
		(0.1208)	(0.1441)	(0.0668)		
17	Textile	−0.7809***	0.8860***	−0.0200	180	0.8773
		(0.0772)	(0.0315)	(0.0239)		
18	Textile wearing apparel, etc.	−0.5273***	0.9245***	0.0653	27	0.9097
		(0.1345)	(0.0828)	(0.0536)		
19	Leather, etc.	−0.4610***	0.8897***	−0.0452	90	0.7785
		(0.0901)	(0.0924)	(0.0437)		
20	Timber, wood, bamboo	−0.6740***	0.7005***	0.0528	72	0.8268
		(0.0777)	(0.0685)	(0.0322)		
21	Furniture	−0.5555***	0.8217***	−0.0699	45	0.9198
		(0.0901)	(0.0753)	(0.0684)		
22	Paper products	−0.7136***	0.4840***	0.0528*	45	0.8386
		(0.0670)	(0.0760)	(0.0250)		
23	Printing, reproduction, and recording media	−0.2803**	0.9117***	−0.0482	45	0.9431
		(0.1065)	(0.0554)	(0.0311)		
24	Articles for culture, education, sports	−0.3238**	0.7602***	0.0362	126	0.6465
		(0.1215)	(0.1033)	(0.0304)		
25	Petroleum, coking, nuclear power	−0.6094***	0.8040***	0.0759	36	0.9064
		(0.0872)	(0.1080)	(0.0817)		
26	Raw chemical materials and chemical products	−0.6045***	0.8904***	−0.0208	270	0.8043
		(0.0541)	(0.0458)	(0.0184)		
27	Medicines	−0.3175***	0.4989***	0.0365*	54	0.7837
		(0.0940)	(0.0646)	(0.0183)		
28	Chemical fibers	−0.4152**	0.7422***	−0.0146	63	0.7234
		(0.1270)	(0.0963)	(0.0447)		
29	Rubber	−0.4274***	0.6851***	−0.0323	81	0.6527
		(0.1267)	(0.0898)	(0.0362)		
30	Plastics	−0.6164***	0.9718***	−0.0444	81	0.8532
		(0.0744)	(0.0868)	(0.0251)		
31	Non-metallic mineral products	−0.5255***	0.7926***	−0.0150	270	0.7565
		(0.0703)	(0.0781)	(0.0146)		
32	Ferrous metals	−0.3637**	0.9252***	−0.0649	36	0.8482
		(0.1225)	(0.0926)	(0.0525)		
33	Non-ferrous metals	−0.6812***	1.0312***	−0.0883*	135	0.7981
		(0.0979)	(0.0759)	(0.0380)		
34	Metal products	−0.4436***	0.8207***	−0.0181	162	0.7994
		(0.0775)	(0.0754)	(0.0171)		
35	General purpose machinery	−0.5642***	0.7077***	−0.0278*	279	0.7863
		(0.0532)	(0.0414)	(0.0117)		
36	Special purpose machinery	−0.5344***	0.8323***	−0.0530*	378	0.7739
		(0.0804)	(0.0598)	(0.0211)		
37	Transport equipment	−0.2476***	0.6464***	−0.0459	207	0.7522
		(0.0711)	(0.0629)	(0.0309)		

(continued)

Table 3. Continued

CIC	Sector	$\Delta\Pi_{jt}$	ΔY_{jt}	Constant	# Obs.	R^2
39	Electrical machinery	−0.6826***	0.8758***	−0.0012	216	0.8377
		(0.0701)	(0.0630)	(0.0198)		
40	Communication equipment, computers, etc.	−0.3269***	0.7512***	−0.1002**	140	0.8363
		(0.0527)	(0.0834)	(0.0317)		
41	Measuring instruments, etc.	−0.2524**	0.6315***	−0.0307	225	0.7109
		(0.0817)	(0.0617)	(0.0475)		
42	Artwork and other manufacturing	−0.5954***	0.8637***	0.0213	108	0.8554
		(0.0949)	(0.0497)	(0.0294)		

Note: OLS regression. Robust standard errors are in parenthesis. ΔN_{jt} four-digit sectoral employment variation; $\Delta\Pi_{jt}$ four-digit sectoral productivity growth; ΔY_{jt} four-digit sectoral sales growth. Year dummies are included in all estimations. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P<0.01$; **$P<0.05$; *$P<0.10$.

Table 4. Sectoral-level employment dynamics (ΔN_{jt}) Equation (2)—export growth

CIC	Sector	$\Delta\Pi_{jt}$	$\Delta EXPORT_{jt}$	Constant	# Obs.	R^2
	All manufacturing	−0.1736***	0.1280***	0.0831***	2904	0.2115
		(0.0437)	(0.0169)	(0.0151)		
13	Food from agriculture products	−0.2524**	0.0763*	0.1391***	105	0.3245
		(0.0828)	(0.0342)	(0.0369)		
14	Food	−0.3675	0.2390**	0.0681	130	0.3676
		(0.2329)	(0.0875)	(0.0526)		
15	Beverages	−0.1822*	0.0329	0.1191***	84	0.2219
		(0.0920)	(0.0226)	(0.0302)		
16	Tobacco	−0.1990	0.1187**	0.1374*	21	0.5197
		(0.1944)	(0.0410)	(0.0560)		
17	Textile	−0.7340***	0.2179*	0.0965*	140	0.4682
		(0.1987)	(0.0943)	(0.0375)		
18	Textile wearing apparel, etc.	−0.1300	0.3380	0.0616	21	0.7112
		(0.1895)	(0.1927)	(0.0374)		
19	Leather, etc.	−0.1492	0.2722**	0.0534	70	0.3273
		(0.1328)	(0.0829)	(0.0487)		
20	Timber, wood, bamboo	−0.6905***	0.0249	0.2606***	56	0.5799
		(0.1099)	(0.0425)	(0.0427)		
21	Furniture	−0.7510***	0.2182***	0.1325***	34	0.8375
		(0.1129)	(0.0366)	(0.0210)		
22	Paper products	−0.3846***	−0.0185	0.1143*	35	0.5061
		(0.1144)	(0.0280)	(0.0572)		
23	Printing, reproduction, and recording media	0.3308	0.5034*	0.0122	35	0.3554
		(0.4636)	(0.2263)	(0.0985)		
24	Articles for culture, education, sports	−0.0014	0.2707***	0.0693	98	0.3627
		(0.1118)	(0.0678)	(0.0416)		
25	Petroleum, coking, nuclear power	−0.2189	0.0292	0.0683	21	0.3486
		(0.2879)	(0.0985)	(0.0673)		
26	Raw chemical materials and chemical products	−0.0890	0.1600***	0.0805*	208	0.2588
		(0.1286)	(0.0377)	(0.0330)		
27	Medicines	−0.1654	0.0300	0.1244***	42	0.2549
		(0.1357)	(0.0687)	(0.0301)		
28	Chemical fibers	−0.2499*	0.3533***	0.1848***	49	0.5821
		(0.1198)	(0.0708)	(0.0507)		
29	Rubber	−0.2912	0.0843	0.0730*	57	0.3557
		(0.1803)	(0.0465)	(0.0332)		

(continued)

Table 4. Continued

CIC	Sector	$\Delta\Pi_{jt}$	$\Delta EXPORT_{jt}$	Constant	# Obs.	R^2
30	Plastics	−0.4728***	0.2137**	0.1298***	63	0.5163
		(0.1029)	(0.0758)	(0.0323)		
31	Non-metallic mineral products	−0.1976	0.0617	0.0947***	205	0.2104
		(0.1073)	(0.0331)	(0.0210)		
32	Ferrous metals	0.2610	0.1028	−0.0025	28	0.3190
		(0.1942)	(0.0815)	(0.0516)		
33	Non-ferrous metals	−0.5080	0.0545	0.0770	101	0.2001
		(0.2784)	(0.0445)	(0.1032)		
34	Metal products	−0.3540**	0.1600***	0.0996***	126	0.3817
		(0.1138)	(0.0468)	(0.0227)		
35	General purpose machinery	−0.2664**	0.0691*	0.0270	217	0.2367
		(0.0815)	(0.0295)	(0.0204)		
36	Special purpose machinery	−0.3835***	0.1057*	0.0461	287	0.2821
		(0.1117)	(0.0424)	(0.0271)		
37	Transport equipment	0.1189	0.1022*	0.0329	145	0.2177
		(0.1750)	(0.0460)	(0.0346)		
39	Electrical machinery	−0.4222*	0.2923*	0.0809*	168	0.4241
		(0.1840)	(0.1380)	(0.0344)		
40	Communication equipment, computers, etc.	−0.0358	0.4237***	−0.0298	108	0.6920
		(0.0981)	(0.1036)	(0.0410)		
41	Measuring instruments, etc.	0.0051	0.1302***	−0.0083	166	0.2215
		(0.1105)	(0.0333)	(0.0534)		
42	Artwork and other manufacturing	−0.2764	0.2148	0.1145*	84	0.3789
		(0.1981)	(0.1708)	(0.0516)		

Note: OLS regression. Robust standard errors are in parenthesis. ΔN_{jt} four-digit sectoral employment variation; $\Delta\Pi_{jt}$ four-digit sectoral productivity growth; $\Delta EXPORT_{jt}$ four-digit sectoral exports growth. Year dummies are included in all estimations. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P < 0.01$; **$P < 0.05$; *$P < 0.10$.

Table 5. Sectoral-level sales growth (ΔY_{jt}) Equation (5)

CIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R^2
	All manufacturing	−0.3999***	2.2096***	3389	0.4120
		(0.0502)	(0.3007)		
13	Food from agriculture products	−0.3746***	3.3838***	120	0.4279
		(0.1107)	(0.4132)		
14	Food	−0.2750	3.8097***	152	0.3631
		(0.2419)	(0.4103)		
15	Beverages	−0.0696	3.5956***	96	0.4864
		(0.0618)	(0.3842)		
16	Tobacco	−0.1413	0.8681	24	0.0539
		(0.2353)	(1.0114)		
17	Textile	−0.5028	3.4455***	160	0.3776
		(0.2863)	(0.3737)		
18	Textile wearing apparel, etc.	0.5447	2.6520***	24	0.4712
		(0.5989)	(0.7066)		
19	Leather, etc.	−0.1250	3.5231***	80	0.4403
		(0.1133)	(0.4744)		
20	Timber, wood, bamboo	0.1690	4.9863***	64	0.7517
		(0.1446)	(0.3549)		

(continued)

Table 5. Continued

CIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R^2
21	Furniture	−0.1153	5.8782***	40	0.5792
		(0.1585)	(1.0115)		
22	Paper products	−0.8346*	3.6052***	40	0.4902
		(0.3720)	(1.0286)		
23	Printing, reproduction, and recording media	−0.0891	3.1436***	40	0.2367
		(0.3410)	(0.8925)		
24	Articles for culture, education, sports	−0.5025***	3.5183***	112	0.4127
		(0.1098)	(0.5161)		
25	Petroleum, coking, nuclear power	−0.1463	3.9839***	32	0.2958
		(0.2046)	(1.1295)		
26	Raw chemical materials and chemical products	−0.3028**	3.5387***	240	0.5019
		(0.1028)	(0.2586)		
27	Medicines	−0.0553	4.2665***	48	0.6790
		(0.2137)	(0.4313)		
28	Chemical fibers	−0.0484	3.6989***	56	0.2964
		(0.2215)	(0.8071)		
29	Rubber	0.0268	3.8619***	72	0.5036
		(0.1505)	(0.4822)		
30	Plastics	−0.1204	3.9038***	72	0.6577
		(0.1617)	(0.3780)		
31	Non-metallic mineral products	−0.3606***	4.1649***	240	0.5951
		(0.0847)	(0.2725)		
32	Ferrous metals	−0.0450	4.5735***	32	0.6546
		(0.2859)	(0.4751)		
33	Non-ferrous metals	−0.4032**	4.6229***	120	0.4659
		(0.1499)	(0.5463)		
34	Metal products	−0.3197*	4.0841***	144	0.5394
		(0.1485)	(0.3282)		
35	General purpose machinery	−0.5464***	4.4158***	248	0.5979
		(0.1525)	(0.3771)		
36	Special purpose machinery	−0.4970**	3.7850***	336	0.4167
		(0.1658)	(0.3447)		
37	Transport equipment	−0.3200	4.0589***	184	0.2140
		(0.1992)	(0.7822)		
39	Electrical machinery	−0.4117***	4.4734***	192	0.5207
		(0.1051)	(0.3063)		
40	Communication equipment, computers, etc.	−0.7244***	5.8529***	125	0.5119
		(0.2156)	(0.6855)		
41	Measuring instruments, etc.	−0.5966***	4.7346***	200	0.3378
		(0.1704)	(0.7199)		
42	Artwork and other manufacturing	0.0542	4.1972***	96	0.3776
		(0.1910)	(0.5691)		

Note: OLS regression without constant. Robust standard errors are in parenthesis. ΔY_{jt} four-digit sectoral sales growth; $\Delta RULC_{jt}$ four-digit sectoral manufacturing RULC growth; $\Delta WorldIncome_t$ world income growth. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P < 0.01$; **$P < 0.05$; *$P < 0.10$.

equilibrium assumption, which, in this case, as rough as it is, appear much better than assuming some exogenous drift thereafter. We also compared the results between OLS regression (with constant) and RTO. We find that (i) the standard errors of the estimates of RULC are very similar in two methods; (ii) the standard errors of the estimates of world income growth are much smaller in RTO than under OLS.

that of price elasticities. The degrees of income elasticity vary across sectors that the most income elastic (around 4 to 5) sectors include the manufacturing of communication equipment and computers, electric machinery, measuring instruments, and transport equipment.

We also estimated the effects of the variations of RULC and world income on *export growth*. Table 6 shows the results. Again, income elasticity dominates price elasticity in determining Chinese sectoral export growth. The most income elastic sectors include metal products, machinery, transport equipment, electrical machinery, communication equipment, computers, and measuring instruments.

Table 6. Sectoral-level export growth ($\Delta EXPORT_{jt}$) Equation (5)

CIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R^2
	All manufacturing	−0.2861**	1.3538	2494	0.1185
		(0.0991)	(0.7369)		
13	Food from agriculture products	−0.1733	2.1071	90	0.0301
		(0.5748)	(1.3790)		
14	Food	−0.6468	3.1172**	112	0.1458
		(0.3441)	(0.9994)		
15	Beverages	−0.9427**	0.6623	72	0.0747
		(0.3505)	(1.8147)		
16	Tobacco	0.0087	1.7506	18	0.0596
		(0.3173)	(2.2438)		
17	Textile	−1.0004	3.3597***	120	0.1431
		(0.6006)	(0.8812)		
18	Textile wearing apparel, etc.	−0.0854	2.6872***	18	0.5824
		(0.2928)	(0.5489)		
19	Leather, etc.	−0.0731	2.5289***	60	0.1782
		(0.2339)	(0.6892)		
20	Timber, wood, bamboo	0.2777	5.0083***	48	0.2534
		(0.5631)	(1.1401)		
21	Furniture	0.1025	4.7932***	30	0.3124
		(0.5776)	(1.2926)		
22	Paper products	−0.5685	−0.9199	30	0.0248
		(0.6198)	(2.6703)		
23	Printing, reproduction, and recording media	0.2193	3.3716**	30	0.1829
		(0.5193)	(1.1322)		
24	Articles for culture, education, sports	−0.5368***	3.2427***	84	0.3335
		(0.1147)	(0.6807)		
25	Petroleum, coking, nuclear power	−0.7607	2.4491	18	0.2496
		(0.5951)	(1.5206)		
26	Raw chemical materials and chemical products	0.2848	4.1778***	178	0.1362
		(0.2975)	(0.7399)		
27	Medicines	−0.1460	3.3119***	36	0.3458
		(0.2433)	(0.6991)		
28	Chemical fibers	−0.3386	3.3711*	42	0.1484
		(0.3267)	(1.5010)		
29	Rubber	−0.8314	2.6221	49	0.1148
		(0.8514)	(1.8380)		
30	Plastics	−0.4792**	3.8852***	54	0.5501
		(0.1672)	(0.4010)		
31	Non-metallic mineral products	0.3800*	3.3200***	176	0.0895
		(0.1589)	(0.8306)		
32	Ferrous metals	0.0872	4.4827**	24	0.3353
		(0.3259)	(1.4059)		
33	Non-ferrous metals	0.1449	0.5339	87	0.0038
		(0.4455)	(2.2945)		

(continued)

Table 6. Continued

CIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R^2
34	Metal products	−0.1287	4.7038***	108	0.4462
		(0.1954)	(0.5004)		
35	General purpose machinery	−0.6804	4.0836***	186	0.2018
		(0.4482)	(0.5555)		
36	Special purpose machinery	−0.4601	5.1026***	247	0.1221
		(0.3089)	(0.9002)		
37	Transport equipment	−0.0706	4.8187**	126	0.0520
		(0.5637)	(1.6493)		
39	Electrical machinery	−0.0697	4.8119***	144	0.2286
		(0.4243)	(0.5816)		
40	Communication equipment, computers, etc.	−1.2105**	7.4075***	93	0.5180
		(0.4145)	(0.9682)		
41	Measuring instruments, etc.	−0.6679**	5.9891***	142	0.2106
		(0.2293)	(1.2364)		
42	Artwork and other manufacturing	0.3236	2.9500***	72	0.2794
		(0.2333)	(0.5706)		

Note: OLS regression without constant. Robust standard errors are in parenthesis. $\Delta EXPORT_{jt}$ four-digit sectoral exports growth; $\Delta RULC_{jt}$ four-digit sectoral manufacturing RULC growth; $\Delta WorldIncome_t$ world income growth. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P < 0.01$; **$P < 0.05$; *$P < 0.10$.

Third, we estimated the sales/or exports dynamics equation augmenting with the variation of sectoral innovativeness (Equation 6), proxied by the growth of the share of Chinese patents in the non-US assignee's ones. The estimates are shown in Table 7. Together, Table 8 shows the ordinary least squares (OLS) estimates for the export dynamics equation. The variation of innovativeness in Chinese manufacturing sectors seems neither contributes to sales growth nor exports growth, but, to repeat, our data refer to a stage of catching-up which by now is mostly over.

6.2 Firm-level evidence

6.2.1 The econometric strategies

Let us turn to firm-level data to analyze the drivers of manufacturing employment through a three-step estimation in line with the theoretical framework of Section 3.2. In the first step, firm-level employment dynamics is jointly determined by productivity growth and sales growth. In the second step, we estimate the replicator-type dynamics linking firm's relative competitiveness, the dynamics of the overall market, and firm's sales growth. In the third step, we integrate replicator-type dynamics into the first step, directly linking firm's relative competitiveness, sectoral sales, and productivity dynamics with employment growth (adding also product innovation and investment). Finally, we estimate the dynamic version of Kaldor–Verdoorn law. We resort to an autoregressive distributed lag model that enables us to estimate both the short-run and the long-run effects. We estimate the models for each four-digit sector to ideally identify the level of competition, where replicator dynamics operates. At least as important, this regression framework also allows to control both for unobserved heterogeneity and for endogeneity of all our main regressors through a "system GMM" estimation (Blundell and Bond, 1998).[26]

6.2.2 Step 1: Employment dynamics

In the first step let us simply account for firm-level employment dynamics ($\Delta n_{i,t}$) as the joint outcome of productivity growth ($\Delta \pi_{i,t}$) and sales growth ($\Delta g_{i,t}$). Employment growth rates vary path-dependently with contemporaneous and past productivity and sales dynamics which reads:

26 The dynamic panel estimations were estimated using the Stata command xtabond2, written by David Roodman (Roodman, 2009). Blundell and Bond (1998) have experimented via Monte Carlo studies that this estimator is preferable to GMM difference estimator.

Table 7. Sectoral-level sales growth (ΔY_{jt}) Equation (6)

ISIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	$\Delta Patent_{jt}$	# Obs.	R^2
	All manufacturing	−0.3251***	3.1001***	0.0018	908	0.6464
		(0.0949)	(0.2209)	(0.0082)		
15	Food products and beverage	−0.0383	3.7216***	−0.0110	127	0.6745
		(0.0999)	(0.2591)	(0.0117)		
16	Tobacco	0.2575	0.6598	0.0113	8	0.1972
		(0.2453)	(0.8479)	(0.0665)		
17	Textile	−0.0801	3.5598***	0.0054	56	0.6666
		(0.1998)	(0.4102)	(0.0225)		
18	Wearing apparel, dressing, and dyeing of fur	−0.1416	3.1763**	0.0872	16	0.7623
		(0.2138)	(1.0847)	(0.1316)		
19	Tanning and dressing of leather, manufacturing	0.0930	3.4483***	0.0495	23	0.8839
	of luggage, handbags, etc.	(0.1513)	(0.3690)	(0.0304)		
20	Wood and wood products	0.1891	4.5522***	−0.0006	30	0.7958
		(0.2843)	(0.4325)	(0.0128)		
21	Paper and paper products	−0.0764	3.9369***	0.0405*	16	0.9154
		(0.2028)	(0.5110)	(0.0205)		
22	Publishing, printing, and reproduction	−0.2566	1.4286	0.0908	24	0.1662
	of recorded media	(0.4701)	(1.4820)	(0.1532)		
23	Coke, refined petroleum products,	−0.2619*	3.5028***	0.0623***	24	0.7316
	and nuclear fuel	(0.1262)	(0.5684)	(0.0181)		
24	Chemical and chemical products	−0.1876**	3.4560***	0.0313	72	0.7468
		(0.0650)	(0.2722)	(0.0192)		
25	Rubber and plastic products	−0.3250*	3.9810***	0.0018	23	0.9173
		(0.1618)	(0.3212)	(0.0159)		
26	Other non-metallic mineral products	−0.1509	4.2416***	0.0194	63	0.8914
		(0.1053)	(0.2305)	(0.0125)		
27	Basic metals	−0.3589*	4.3760***	0.0512	32	0.8390
		(0.1479)	(0.5277)	(0.0687)		
28	Fabricated metal products	−0.4095	4.5638***	−0.0152	40	0.8029
		(0.2259)	(0.4176)	(0.0194)		
29	Machinery and equipment	−0.6351***	4.0282***	−0.0359*	118	0.6197
		(0.1929)	(0.3060)	(0.0171)		
30	Office, accounting and computing machinery	−0.0345	4.3684*	0.3837	8	0.8219
		(0.1079)	(1.7949)	(0.3013)		
31	Electrical machinery and apparatus n.e.c.	−0.3737**	4.6059***	0.0314	48	0.8543
		(0.1212)	(0.3652)	(0.0210)		
32	Radio, TV, and communication equipment	−0.4287***	4.7009***	0.0788	24	0.8815
	and apparatus	(0.0933)	(0.8688)	(0.0898)		
33	Medical, precision, and optical instruments,	−0.3791***	3.9597***	0.0920	40	0.8413
	watches and clocks	(0.0785)	(0.5186)	(0.0778)		
34	Motor vehicles, trailers, and semi-trailers	−0.2525	4.1594***	0.0917*	24	0.8200
		(0.1361)	(0.5808)	(0.0456)		
35	Other transport equipment	−0.7190	3.9348***	−0.0630	44	0.4021
		(0.3711)	(0.9903)	(0.0557)		
36	Furniture and others	0.1649	3.8030***	−0.0008	48	0.7276
		(0.2021)	(0.3520)	(0.0204)		

Note: OLS regression without constant. Robust standard errors are in parenthesis. $\Delta RULC_{jt}$ four-digit sectoral RULC growth; $\Delta WorldIncome_t$ world income growth; $\Delta Patent_{jt}$ growth of the percentage share of Chinese patents in the foreign patent granted by the USPTO. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P < 0.01$; **$P < 0.05$; *$P < 0.10$.

Table 8. Sectoral-level export growth ($\Delta EXPORT_{jt}$) Equation (6)

ISIC	Sector	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	$\Delta Patent_{jt}$	# Obs.	R^2
	All manufacturing	−0.4294	1.6378**	0.0319	677	0.2654
		(0.3592)	(0.6239)	(0.0285)		
15	Food products and beverage	−0.5383*	1.3957*	0.0361	94	0.1327
		(0.2695)	(0.6883)	(0.0272)		
16	Tobacco	0.4333*	0.5359	0.0057	6	0.4299
		(0.2202)	(1.2037)	(0.1007)		
17	Textile	−0.0434	1.9522***	0.0066	42	0.4228
		(0.1841)	(0.4309)	(0.0295)		
18	Wearing apparel, dressing, and dyeing of fur	−0.3001	0.0133	0.3537	12	0.6359
		(0.2549)	(1.8319)	(0.1908)		
19	Tanning and dressing of leather;	−0.2040	2.1342***	0.0865	17	0.7077
	manufacturing of luggage, handbags, etc.	(0.2591)	(0.4981)	(0.0542)		
20	Wood and wood products	0.0537	3.7377***	0.0470	22	0.4779
		(0.6670)	(0.9716)	(0.0475)		
21	Paper and paper products	−0.5528	4.0459*	0.0067	12	0.5360
		(0.8777)	(1.8249)	(0.0823)		
22	Publishing, printing, and reproduction of	0.6047	1.4024	0.1534	18	0.1408
	recorded media	(0.8263)	(1.9867)	(0.1511)		
23	Coke, refined petroleum products, and	−0.6215	1.8061	0.0706*	18	0.3310
	nuclear fuel	(0.5867)	(1.6136)	(0.0284)		
24	Chemical and chemical products	−0.4498**	3.4953***	0.0285	54	0.6247
		(0.1745)	(0.4577)	(0.0182)		
25	Rubber and plastic products	−0.5963	3.9078***	−0.0211	17	0.8294
		(0.3520)	(0.6645)	(0.0305)		
26	Other non-metallic mineral products	−0.3627	2.9418***	−0.0200	47	0.1906
		(0.4448)	(0.7174)	(0.0389)		
27	Basic metals	−0.6460	3.6810***	0.0795	24	0.5456
		(0.3497)	(0.8436)	(0.1458)		
28	Fabricated metal products	−0.4619	3.9784***	−0.0219	30	0.5330
		(0.5173)	(0.7256)	(0.0326)		
29	Machinery and equipment	−1.4630	3.9738***	0.0144	88	0.4195
		(0.8913)	(0.6575)	(0.0430)		
30	Office, accounting and computing machinery	−0.0533	5.2227*	0.8330**	6	0.9224
		(0.3260)	(2.1377)	(0.3050)		
31	Electrical machinery and apparatus n.e.c.	−0.7022***	4.6842***	−0.0109	36	0.7877
		(0.1952)	(0.3428)	(0.0251)		
32	Radio, TV, and communication equipment	−0.3681**	3.8336***	0.2773***	18	0.9029
	and apparatus	(0.1305)	(0.9936)	(0.0834)		
33	Medical, precision, and optical instruments,	−0.2136	1.3197	0.4252*	30	0.4150
	watches and clocks	(0.3406)	(2.2577)	(0.2129)		
34	Motor vehicles, trailers, and semi-trailers	0.1333	5.8306***	0.0386	18	0.6362
		(0.4004)	(1.2500)	(0.0388)		
35	Other transport equipment	0.1404	10.0552***	0.2117	32	0.1666
		(1.9009)	(3.0343)	(0.3579)		
36	Furniture and others	−0.1843	3.4836***	−0.0068	36	0.6323
		(0.2260)	(0.4864)	(0.0294)		

Note: OLS regression without constant. Robust standard errors are in parenthesis. $\Delta EXPORT_{jt}$ four-digit sectoral exports growth; $\Delta RULC_{jt}$ four-digit sectoral RULC growth; $\Delta WorldIncome_t$ world income growth; $\Delta Patent_{jt}$ growth of the percentage share of Chinese patents in the foreign granted by the USPTO. Two-digit sectoral dummies are included in the "all manufacturing" estimation.

***$P < 0.01$; **$P < 0.05$; *$P < 0.10$.

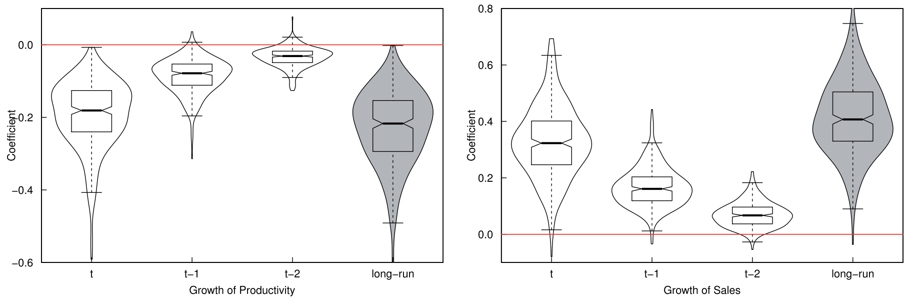

Figure 4. Employment growth model: system GMM results of Equation (10). Distributions of the estimated coefficients and the long-run effects of labor productivity growth and sales growth, across 284 four-digit sectors. The shaded-violins denote the long-run effects. Only four-digit sectors with a number of firms greater than 160.

$$\Delta n_{i,t} = \sum_{k=1}^{K} \eta_k \Delta n_{i,t-k} + \sum_{l=0}^{L} \alpha_l \Delta \pi_{i,t-l} + \sum_{l=0}^{L} \beta_l \Delta g_{i,t-l} + \rho CONTROL_{i,t-1} + \epsilon_{i,t}, \tag{10}$$

where control variables involve (lagged) firm size (in terms of employment) and age.[27] The long-run coefficients are calculated from the short-run ones according to formula:

$$x_{long-run} = \frac{\sum_{l=0}^{L} x_l}{1 - \sum_{k=1}^{K} \eta_k}, \tag{11}$$

where $x \in \alpha, \beta$.

To decide how many lags in the dependent variable to be included into the model, we test the autoregressive structure for employment growth for each four-digit sector. Lags of employment growth of an order higher than two are not significant.[28] Hence, we choose $K = 2$ and $L = 2$ after some experiments. We use system GMM to estimate Equation (10) for each four-digit sector.[29]

Figure 4 shows the distributions of system GMM estimates and the corresponding long-run effects over four-digit sectors. Table 9 shows the median of the distributions of coefficient estimates. As a robustness check, we estimate the same model including year dummies. The results are very similar.[30] Contemporaneous and lagged productivity growth display a remarkable labor-displacing effect. Conversely, contemporaneous and lagged sales growth shows significant contributions to employment growth.

6.2.3 Step 2: Replicator dynamics

Firm's sales can be obviously written as the product of the overall market size M_t and firm's market share $S_{i,t}$. Firm's sales growth is the log difference of sales of 2 consecutive years $\Delta g_{i,t} = \ln(S_{i,t}M_t) - \ln(S_{i,t-1}M_{t-1})$.

27 Here we do not control for year dummies, because we focus on the *absolute* employment growth, productivity growth, and sales growth. But we also test the model including year dummies as a robustness check. The results are very similar.

28 The empirical evidences, in the literature, of the autocorrelation structure of growth rates are mixed: Coad and Hölzl (2009) shows negative autocorrelation to the order 2 in terms of employment growth, which is very similar to the finding here.

29 The algorithm for choosing instruments is as follows. First, we treat lagged employment growth, productivity growth, and sales growth as endogenous variables. Their instruments are set from lag 2 to lag 5. We check the P values of AR(2) test and Hansen test after running the system GMM. Second, if either of the two tests are rejected (AR(2) $P < 0.1$ or Hansen $P < 0.45$), we adopt further lags as instruments: lag 3 $\sim$lag 6 for lag employment growth, lag 2 $\sim$lag 5 for other variables. Then, we check again the P values of AR(3) and Hansen tests. Third, if either of these two tests are rejected at the second step, we instrument all independent variables using lag3 $\sim$lag6.

30 The same applies in all estimations in this section. Distributions of GMM estimates are available upon request.

Table 9. Summary statistics (median) of the distributions in Figure 4

Variables	t	t−1	t−2	Long-run
Productivity growth	−0.181***	−0.079***	−0.031***	*−0.217****
Sales growth	0.323***	0.161***	0.067***	*0.407****

Note: Median of the distribution of estimates based on the baseline model. Wilcoxon signed-rank test for zero median. Significant at ***$P<0.01$; **$P<0.05$; *$P<0.10$.

Hence, $\Delta g_{i,t} = \Delta s_{i,t} + \Delta m_t$. The growth rate of sales of firm i at time t is clearly the sum of the growth rates of its market share and the growth rate of the overall market size. Here, we measure market size at four-digit sectoral level. In turn the dynamics of a firm's market share ($\Delta s_{i,t}$) can be interpreted using a replicator-type process as driven by the firm's relative competitiveness. Therefore:

$$\Delta g_{i,t} = \sum_{k=1}^{K} \eta_k \Delta g_{i,t-k} + \sum_{l=0}^{L} \alpha_l \tilde{X}_{i,t-l} + \gamma \Delta m_t + \rho CONTROL_{i,t-1} + \epsilon_{i,t}, \tag{12}$$

where $\Delta g_{i,t}$ absolute sales growth of firm i at time t, $\tilde{X}_{i,t}$ is relative competitiveness which shall be defined below, and Δm_t is the growth of market size. We control for firm's (lagged) size and age.[31]

To decide how many lags of dependent variable to be included into the model, we test the autoregressive structure for sales growth for each four-digit sector. Lags on sales growth of an order higher than two are not significant.[32]

We use two measures to proxy firm's relative competitiveness: relative productivity level (i.e. a broader proxy for firm's technological and organizational advantages) and relative productivity growth rate (i.e. process innovation).

First, let us estimate Equation (12) using *relative productivity level* as a proxy for relative competitiveness.[33] Here, we choose $K=2$ and $L=1$ after some experiments. We use system GMM for each four-digit sector. Figure 5 shows the distribution of the estimates. Table 10 shows the median of the distribution of coefficient estimates for the baseline model. The contemporaneous productivity level displays significant positive effect on sales growth; however, the lagged one shows some negative effect (indeed as in Bottazzi *et al.*, 2010 and Dosi, Moschella *et al.*, 2015). The long-run effect of relative productivity level on sales growth is positive and significant. The growth rate of the overall market reveals a mild positive effect on firm's sales growth.

Second, we use *relative productivity growth* as a proxy for relative competitiveness. Here, we choose $K=2$ and $L=2$ after some experiments, and, again, system GMM to estimate Equation (12) for each four-digit sector. Figure 6 shows the distribution of estimates across 284 four-digit sectors, and Table 11 shows the median of the distributions. The positive effect of relative productivity growth on sales growth—in tune with previous studies—is very significant both in the short run and in the long run. The effect of overall market size growth on firm-level sales growth seems significant.

6.2.4 Step 3: Integrate replicator dynamics into employment dynamics model

Finally, we plug the model of Step 2 into Step 1 and add other variables (product innovation and investment intensity) to estimate directly the effect of firm's relative competitiveness, product innovation, and investment intensity on employment growth:

$$\begin{aligned}\Delta n_{i,t} = &\sum_{k=1}^{K} \eta_k \Delta n_{i,t-k} + \sum_{l=0}^{L} \alpha_l \tilde{X}_{i,t-l} + \sum_{l=0}^{L} \xi_l NEWPROD_{i,t-l} + \sum_{l=0}^{L} \theta_l I_{i,t-l}, \\ &+ \gamma \Delta m_t + \zeta \Delta \Pi_{t-1} + \rho CONTROL_{i,t-1} + \epsilon_{i,t}\end{aligned} \tag{13}$$

31 Here, in our baseline estimation, we do not control for year dummies, because we include the growth of market size of four-digit sector which is perfectly collinear with year dummies. However, in the robustness check, the estimates of the models with year dummies are very similar to our baseline model.

32 Notice that, a comparison of the estimation methods for the autoregressive structure of sales growth is available upon request.

33 In line with Bottazzi *et al.* (2010) and Dosi, Moschella *et al.* (2015).

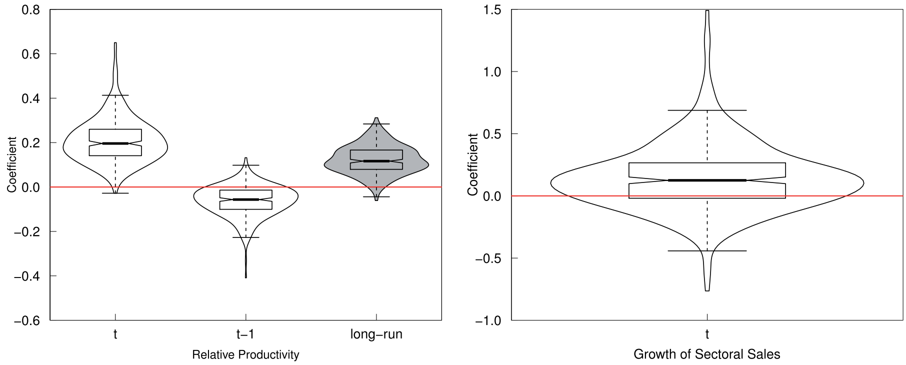

Figure 5. Sales growth model: system GMM results of Equation (12)—productivity. Distributions of the estimated coefficients and the long-run effects of (relative) labor productivity *level* and sectoral sales growth, across 284 four-digit sectors. The shaded-violins denote the long-run effects. Only four-digit sectors with a number of firms greater than 160.

Table 10. Summary statistics (median) of the distributions in Figure 5

Variables	t	$t-1$	Long-run
Relative productivity level	0.196***	−0.057***	*0.117****
Sectoral sales growth	0.125***		

Note: Median of the distribution of estimates based on the baseline model. Wilcoxon signed-rank test for zero median. Significant at $^{***}P < 0.01$; $^{**}P < 0.05$; $^{*}P < 0.10$.

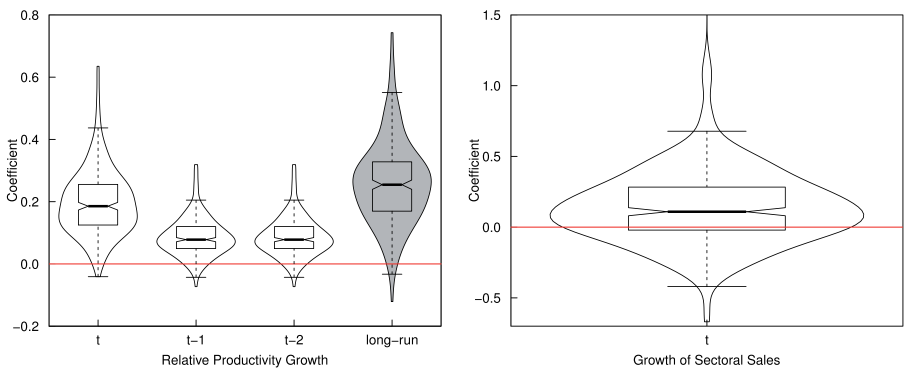

Figure 6. Sales growth model: system GMM results of Equation (12)—productivity growth. Distributions of the estimated coefficients of (relative) labor productivity *growth* and sectoral sales growth, across 284 four-digit sectors. The shaded-violins denote the long-run effects. Only four-digit sectors with a number of firms greater than 160.

where $\tilde{X}_{i,t}$ is *relative competitiveness*, either in terms of relative productivity level or relative productivity growth. We also include sectoral productivity growth $\Delta\Pi_{t-1}$ and sectoral sales growth Δm_t to control for sector-wide dynamics in process technology and market size.

First, let us consider relative productivity levels as proxy for competitiveness (see Figure 7 and Table 12). Firm's *relative* productivity *levels* display significant contemporaneous negative effect on employment growth. However, the lagged and long-run effects are significantly positive. Product innovation does not show significant effect on employment growth (but recall the caveats above). Investment intensity seems display a significant positive effect on

Table 11. Summary statistics (median) of the distributions in Figure 6

Variables	t	t–1	t–2	Long-run
Relative productivity growth	0.186***	0.078***	0.031***	*0.255****
Sectoral sales growth	0.109***			

Note: Median of the distribution of estimates based on the baseline model. Wilcoxon signed-rank test for zero median. Significant at ***$P<0.01$; **$P<0.05$; *$P<0.10$.

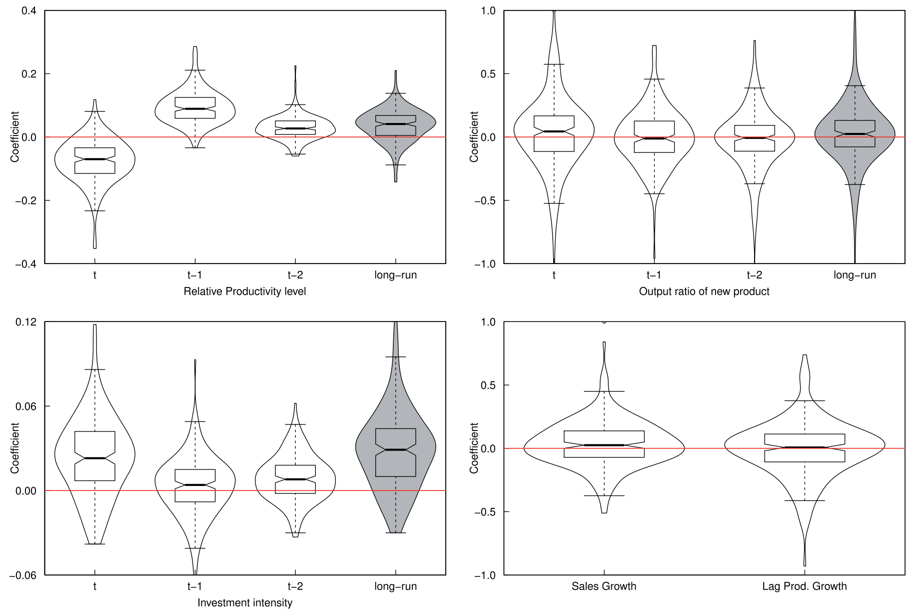

Figure 7. Employment growth model: system GMM results of Equation (13)—productivity level. Distributions of the estimated coefficients and the long-run effects of (relative) labor productivity *level* (top left), new product ratio (top right), investment intensity (bottom left), and sectoral sales growth and productivity growth (bottom right), across 177 four-digit sectors. The shaded-violins denote the long-run effects. Only four-digit sectors with a number of firms greater than 160.

Table 12. Summary statistics (median) of the distribution in Figure 7

Variables	t	t–1	t–2	Long-run
Relative productivity level	−0.070***	0.089***	0.027***	*0.041****
New product	0.044**	−0.012	−0.007	*0.024**
Investment intensity	0.023***	0.004**	0.008***	*0.029****
Sectoral sales growth	0.025***			
Sectoral productivity growth	0.007			

Note: Median of the distribution of estimates based on baseline model. Wilcoxon signed-rank test for zero median. Significant at ***$P<0.01$; **$P<0.05$; *$P<0.10$.

employment growth. Sectoral sales growth shows a mild positive effect on employment growth, while sectoral productivity growth does not display any role.

Second, let us use relative productivity growth as proxy for competitiveness (results see Figure 8 and Table 13). Such a variable has a negative and significant effect on employment growth both in the short run and in the long run. Product innovation displays a very mild positive effect in the short-run. Investment intensity has a significant positive

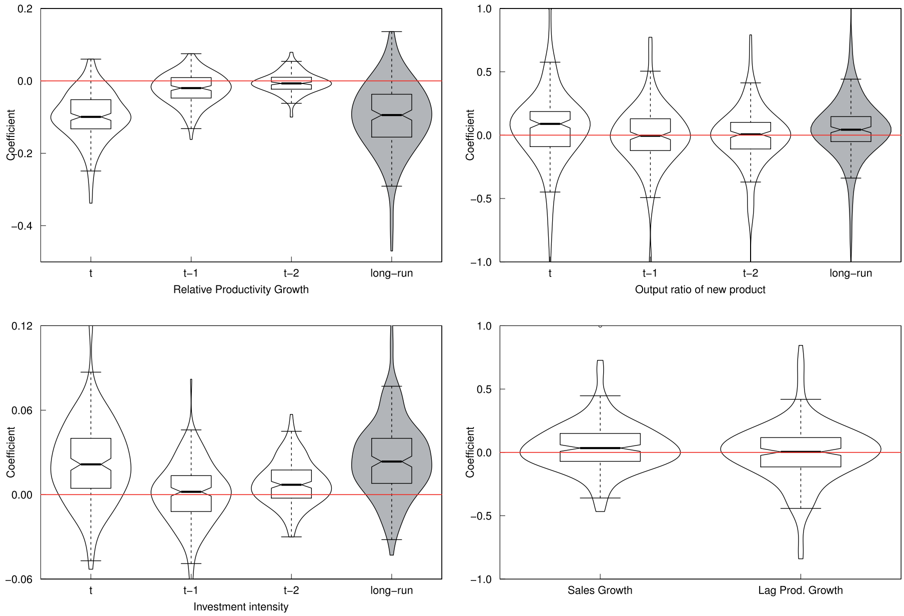

Figure 8. Employment growth: system GMM results of Equation (13)—productivity growth. Distributions of the estimated coefficients and the long-run effects of (relative) labor productivity *growth* (top left), new product ratio (top right), investment intensity (bottom left), and sectoral sales growth and productivity growth (bottom right), across 177 four-digit sectors. The shaded-violins denote the long-run effects. Only four-digit sectors with a number of firms greater than 160.

Table 13. Summary statistics (median) of the distribution in Figure 8

Variables	*t*	*t*–1	*t*–2	Long-run
Relative productivity growth	−0.100***	−0.020***	−0.007***	*−0.095****
New product	0.089***	−0.005	0.007	*0.043****
Investment intensity	0.022***	0.002	0.007***	*0.024****
Sectoral sales growth	0.034***			
Sectoral productivity growth	0.004			

Note: Median of the distribution of estimates based on the baseline model. Wilcoxon signed-rank test for zero median. Significant at $^{***}P < 0.01$; $^{**}P < 0.05$; $^{*}P < 0.10$.

effect on employment growth. Sectoral sales growth displays a very mild positive effect on employment growth, while sectoral productivity growth does not show any effect at all.

According to the matching results between our firm-level data set and firm’s *patenting* activities in the USPTO, 99% of Chinese patents granted in the USPTO are from the manufacturing of communication equipment computers, etc. (CIC 40) during the period 1998–2007. We further investigate the effect of patenting activities on firm’s employment growth for each four-digit sector within the broad CIC 40 sector. (There are 16 four-digit sectors in CIC 40.) We create a time invariant dummy variable distinguishing patenting firms from the others, which equals to 1 if a firm has been granted a patent for at least 1 year. We re-estimate Equation (13) including also the patenting dummies. The patenting one displays significant positive effect on firm’s employment growth only in two four-digit sectors, which are the manufacturing of communication exchange equipment (CIC 4012) and semiconductor discrete devices (CIC 4052).[34]

34 Results are available upon request.

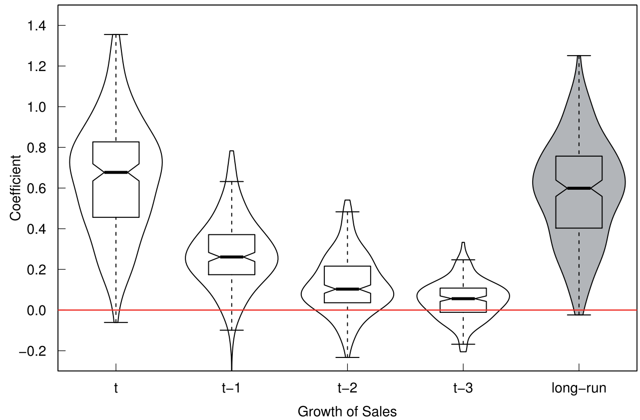

Figure 9. Dynamic Verdoorn–Kaldor law: system GMM results of Equation (14). Distributions of the coefficients and the long-run effects of growth rates of sales across 193 four-digit sectors. The shaded-violins denote the distribution of long-run effects. Only four-digit sectors with a number of firms greater than 160.

Table 14. Summary statistics (median) of the distribution in Figure 9

Variables	t	$t-1$	$t-2$	$t-3$	Long-run
Sales growth	0.677***	0.261***	0.103***	0.056***	*0.599****

Note: Median of the distribution of estimates based on the baseline model. Wilcoxon signed-rank test for zero median. Significant at $^{***}P<0.01$; $^{**}P<0.05$; $^{*}P<0.10$.

6.2.5 Verdoorn–Kaldor law: increasing returns from increasing absolute competitiveness

We have shown a very significant contribution of sales growth to firm-level employment growth for narrowly defined sectors. Here, let us consider the reverse relation and estimate the Verdoorn–Kaldor coefficients, that is the effect of sales growth on productivity growth due to increasing returns:

$$\Delta\pi_{i,t} = \sum_{k=1}^{K} \eta_k \Delta\pi_{i,t-k} + \sum_{l=0}^{L} \beta_l \Delta g_{i,t-l} + \rho CONTROL_{i,t-1} + \epsilon_{i,t,} \tag{14}$$

where control variables involve (lagged) firm size (in terms of employment) and age.[35] Here, we take $K=3$ and $L=3$. Three lags of productivity growth are included in the model to obtain consistent estimates, while the controlled lagged dependent variables display significant negative effects. Sales growth contributes significantly to productivity growth both in the short and long run (the distribution of coefficient estimates is shown in Figure 9, and the median values are shown in Table 14). To summarize, the result shows very significant increasing returns just mitigated by some regression-to-the-mean.

7. Conclusions

This article contributes to the analysis of employment dynamics both at the sectoral level and at the firm level for Chinese manufacturing during the period of a striking economic boom.

First, employment dynamics at the sectoral level is the joint outcome of the dynamics of labor productivity growth, which we take as a broad measure of technological progress on the one hand, and absolute competitiveness

35 We do not include year dummies in order to address the association between *absolute* growth of sales and *absolute* growth of productivity. But we also test the model including year dummies as a robustness check. The results are very similar.

in the international markets, proxied by exports growth, on the other. The results reveal both a powerful labor displacement effect of productivity growth and a significant positive contribution of sales and export growth to employment. Together, Chinese sectoral absolute competitiveness is primarily associated with specialization profile characterized by high elasticities to world income growth. In turn such specialization patterns have been shaped by long-term industrial policies (Dahlman, 2009) and are rooted in profound processes of catching-up, imitation, "creative adaptation," and organizational innovation (more in Yu *et al.*, 2015 and Yu *et al.*, 2017).

Second, we considered employment dynamics at the firm level as jointly affected by (relative) productivity level/growth, product innovation, investment intensities, as well as sectoral sales and productivity dynamics. We found that relative productivity levels (i.e. a higher relative competitiveness of the firms) contribute to employment growth in the long run, while process innovation (proxied by productivity *growth*) displays significant labor displacement effect.[36] Firm's investment positively contributes to employment growth. Moreover, firm's sales growth plays a two-sided role: while it contributes directly to employment growth, it also drives productivity growth (through increasing returns), thus moderating its labor-creating effect.

Third, the insignificant role of innovativeness (proxied by product innovation and patenting activities) suggests that in the period covered by our data, China had not yet reached the technological frontier in most sectors. It is a condition, we conjecture, which has been rapidly changing thereafter.

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36 Recall our quite expansive notion of "process innovation" which implicitly captures also various forms of technological and organizational catching-up and changes in management and organizational routines.

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Appendix

A Table Appendix

Table A1. Summary statistics (total) of the Chinese manufacturing firm-level data set

Year	Number of Firms	Value added	Sales	Output	Employment	Sales value	Export (%)	Original value of fixed assets
1998	148,661	1.52	5.48	5.94	50.72	5.72	18.34	4.48
1999	146,075	1.68	5.96	6.37	47.36	6.17	18.14	4.85
2000	147,246	1.96	7.14	7.48	45.83	7.29	19.43	5.17
2001	155,659	2.22	7.99	8.40	44.95	8.18	19.38	5.54
2002	165,793	2.62	9.37	9.79	45.87	9.58	20.51	5.95
2003	181,001	3.40	12.38	12.72	48.71	12.44	21.30	6.59
2004	258,869	4.80	17.14	17.74	56.52	NA	NA	7.82
2005	250,952	5.71	21.34	21.74	59.21	21.29	22.11	9.02
2006	278,644	7.23	26.99	27.40	63.32	26.85	22.29	10.54
2007	312,284	9.37	34.70	35.27	68.38	34.56	21.08	12.35

Note: All values are denoted in trillion RMB and employment in millions of workers. All manufacturing firms are included. Export is the percentage of export in total sales value. Output and value added in year 2004 are not available. We proxy output as the sum of sales and the difference of inventories between year-end and year-beginning.

Table A2. Summary statistics (mean) of the Chinese manufacturing four-digit sectoral-level data set

Year	Number of four-digit Sectors	Employment	Sales	Labor productivity	Exports	Wage per employee	Employment growth	Sales growth	Labour productivity growth	Exports growth	Growth of (nominal) wage per employee
1998	424	96,711	11	36	2	7	NA	NA	NA	NA	NA
1999	423	103,649	13	40	3	8	0.067	0.186	0.120	0.095	0.060
2000	424	100,313	16	47	3	9	−0.030	0.125	0.141	0.247	0.126
2001	423	100,470	18	53	4	10	0.010	0.136	0.126	0.114	0.086
2002	424	102,602	21	61	5	11	0.043	0.178	0.141	0.152	0.077
2003	424	108,984	28	71	6	12	0.075	0.242	0.153	0.287	0.098
2004	424	117,450	37	89	NA	13	0.064	0.202	0.200	NA	0.139
2005	424	135,751	49	93	11	15	0.160	0.303	0.089	NA	0.144
2006	424	145,965	62	108	14	18	0.081	0.239	0.158	0.218	0.141
2007	424	143,572	75	129	16	21	−0.025	0.158	0.178	0.059	0.189

Note: Values of sales and exports are denoted in billion RMB; labor productivity and wage per employee are denoted in 1000 RMB. Labor productivity is in 1998 constant price. Growth rates recalculated as log differences of real value.

Source: The cleaned firm-level data set.

B The procedure for constructing firm-level and sectoral proxies for innovativeness

To identify whether the firms in the NBS database hold patents in the USPTO during 1998–2007 (according to the application filing dates), we match several databases as follows. (i) The PATSTAT (version 2014a) has been matched with Orbis to sort out patents filed in the USPTO by Chinese firms during 1998–2007. The firms are identified by the BvD ID. We have identified 2828 patents (exclude design patents) in the USPTO which are filed by Chinese firms.

Table B3. Number of patents in the USPTO filed by Chinese firms

Year	Number of patents in PATSTAT	Number of matched patents between PATSTAT and NBS firms
1998	3	0
1999	0	0
2000	0	0
2001	21	8
2002	36	25
2003	104	92
2004	290	270
2005	481	412
2006	870	779
2007	1023	910
Total	2828 [96 firms]	2496 [52 firms]

Note: Years refer to the application filing year. Exclude design patents.

(ii) We get the BvD ID and NBS ID matches from the Oriana database (version 2017 January, BvD Asian-pacific regions). (iii) We match NBS firm-level database with PATSTAT through the NBS ID and BvD ID. Finally, as shown in Table B3, we get the annual number of patents filed by NBS Chinese firms in the USPTO. We successfully matched 2496 patents with NBS firms (matching rate 88%), among which 2464 patents (99%) are filed by firms in the telecommunication equipment and computers manufacturing (CIC 40).[37] Therefore, we only include patent dummy as an additional explanatory variable in the firm-level employment growth model for each four-digit sectors in telecommunication manufacturing (CIC 40).

To estimate the effect of innovativeness at *sectoral* level, we merge our four-digit aggregated Chinese manufacturing data set with the patent data set (Source: PATSTAT version 2014a, USPTO patents only) based on the procedures: (i) convert four-digit CIC into four-digit ISIC (Rev3) codes; (ii) match the four-digit patent IPC code with the four-digit ISIC (Rev3) code using the Lybbert and Zolas (2014) method (we use the probability weight) and count the number of Chinese, non-US, and world patents in each four-digit ISIC sector, respectively; (iii) merge the above two data sets by the unique ISIC code.

37 Among the others, 12 patents are from medicines (CIC 27), 9 are from electrical machinery (CIC 39), 9 are from measuring instruments (CIC 41), 1 is from printing, reproduction, and recording media (CIC 23), and 1 is from special purpose machinery (CIC 36).