Technological catching-up, sales dynamics and employment growth: evidence from China's Manufacturing[*]

Giovanni Dosi[1,2] and Xiaodan Yu[†1,2,3]

[1]Institute of Economics, Scuola Superiore Sant'Anna, Pisa, Italy
[2]IBIMET-CNR, Firenze, Italy
[3]Nottingham University Business School China, University of Nottingham Ningbo China, Ningbo, China

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Abstract

This paper investigates the microeconomics of employment dynamics, using a Chinese manufacturing firm-level dataset over the period 1998-2007. It does so in the light of a scheme of "circular and cumulative causation", whereby firms' heterogeneous productivity gains and 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 labour-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.

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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 labour-saving effect of technological progress can be automatically adjusted by the market (see Freeman, Clark, and Soete, 1982; Vivarelli, 1995; Vivarelli, 2014; Dosi, 1984 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 labour force is endogenously generated by demand creation due to product innovation or expanding existing markets, one the one hand, and continuous labour 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 using 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, fuelled 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; Freeman and Soete, 1994; Dosi, 1984; Dosi, Pavitt, and Soete, 1990; Dosi, Grazzi, and Moschella, 2015; Lee, 2013; Vivarelli and Pianta, 2000; 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 labour cost), 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

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[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.

sales and they are jointly affected by world income growth, variations on sectoral unit labour 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 labour displacement associated with productivity growth as compared to the labour 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, labour demand is largely driven by sectoral sales growth while the growth of productivity is markedly labour displacing, even if it helps cost competitiveness (proxied by relative unit labour cost). 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 labour-displacing effects of productivity growth is 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 do appear to have positive effect on labour demand. Conversely, firms' patenting activities (in the US) do not correlate with employment growth (note however that the surge in Chinese patenting abroad is a quite recent phenomenon).

The paper is organized as follows. Section 2 briefly discusses the state-of-the-art on the evidence both at 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.

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 find 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, 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 detects 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 labour-displacement effect.[6] However, there can be an indirect effect of process innovation on employment, that the increasing productivity may be associated

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[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 scepticism are discussed in Dosi and Grazzi (2006); Dosi and Nelson (2010) and Dosi et al. (2016).

[5]See among the 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 et al. (2015), Zimmermann (2009) and Triguero et al. (2014).

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]

Note that the foregoing results stem implicitly or explicitly from an equilibrium framework whereby labour 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] Π_{jt} is sectoral (weighted-) average labour 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 labour productivity growth. Notice that, labour 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}).

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

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

[8]Here we assume for simplicity sectoral output equals demand.

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 leads to proportional increases of demand).

The relative price of commodities of sector j is a function of sectoral relative unit labour cost (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, relative unit labour cost 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 $\frac{\Delta ULC_{China,jt}}{ULC_{China,jt}} + \frac{\Delta E_t}{E_t} - \frac{\Delta ULC_{World,jt}}{ULC_{World,jt}}$. In comparison with the "world" the dynamics of sectoral *cost advantages/disadvantages* captures the joint effect of wages and labour 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 relative unit labour cost 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) relative unit labour cost, as a proxy of *cost advantages*, which is jointly determined by (the dynamics in) wage gap (measured in international currency) and the dynamics in labour 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 are Chinese patents in the 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 the theoretical interpretation of the sectoral-level employment growth, our firm-level employment dynamics is jointly shaped by the overall market growth, the firm-specific labour productivity,

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[9]Notice that the unit labour cost of sector j in country i (ULC_{jt}) is defined as the ratio between sectoral average wage per employee (W_{ji}) and average productivity (Π_{jt}) is defined as the ratio between real value added and the number of employees).

the dynamics of firm-specific competitiveness (influencing firm's sales growth) within a narrowly defined (4-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 labour productivity growth; $\Delta Y_{ijt}/Y_{ijt}$ 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 performance in the *carriers* of such characters in the relevant population on the other (see, among others, Silverberg et al. (1988); Dosi et al. (1995), and the discussion in Dosi and Nelson (2010). In its linear specification

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

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 (capture the firm's technological and cost advantages) and $\overline{E}_{jt}$ 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 labour productivity are likely to lead to labour shedding, other things being equal. However,

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[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.

second, relative labour 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 dataset 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 to 79 million workers, accounting for about 7.5% to 10.5% of the total employment. Each firm is assigned to a sector according to the 4-digit Chinese industry Classification (CIC) system that closely matches the Standard Industrial Classification (SIC) employed by the U.S. Bureau of Census.[12] Out of the comprehensive set of all firms, we focus on manufacturing firms only (CIC 13 - 42). Table A.1 (in the Appendix) 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 two 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 two consecutive 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 two consecutive years. We use two-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 per-

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[11]Industry if 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 dataset in order 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 two consecutive years.

[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.

Table 1: Summary statistics (mean) on the firm-level dataset (after cleaning).

Year	Number of Firms	Employment	Sales	Labour Productivity	Employment Growh	Sales Growth	Labour Productivity Growth	Ratio of New Product in Output	2-year MA Investment Intensity
1998	108286	379	43 847	44	NA	NA	NA	0.029	NA
1999	125917	348	45 266	48	−0.038	0.016	0.070	0.028	NA
2000	126054	337	53 875	54	−0.022	0.049	0.061	0.029	0.291
2001	138410	307	55 577	59	−0.024	0.007	0.046	0.031	0.269
2002	149189	292	60 690	68	−0.001	0.071	0.083	0.028	0.266
2003	162086	285	73 925	76	0.018	0.129	0.099	0.027	0.253
2004	211534	235	73 162	88	0.013	0.118	0.047	0.034	0.242
2005	238160	242	87 461	97	0.051	0.189	0.154	0.036	0.236
2006	265912	233	98 964	114	0.024	0.178	0.171	0.039	0.229
2007	248299	245	128 191	137	0.032	0.199	0.177	0.038	0.205

Note: Sales are in current price; labour productivity and investment intensity are in 1998 constant price; unit 1000 RMB. Growth rates are calculated as log differences of real value, at 1998 constant price.

centage 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 provide 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 US identified through a procedure discusses in Appendix B.[17]

4.3. Sectoral data

For our sectoral analysis, our firm-level dataset has been aggregated at 4-digit sectoral level, in order to obtain total (real) value-added, total employment, total (real) sales, total (real) exports for each 4-digit sector. Sectoral employment growth, sales growth and labour productivity growth are calculated as above. Table A.2 provide basic descriptive statistics of the main variables used in the empirical analysis. The growth rate of relative unit labour cost of sector j at time t can be derived based on: a) the growth rate of Chinese unit labour cost of sector j at time t; b) the growth of trade-weighted bilateral exchange rate index (i.e. trade-weighted "world currency" per Chinese yuan);[18] c) growth of world unit labour 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]

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[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 are not available for years 2001 and 2004, we fill in the gaps using the averages between the the values of previous year and the next year for each firm.

[17] A dummy variable distinguishes firms holding patent for at least one year in the USPTO during 198-2007.

[18] To calculate it, we use two variables 1) G7 trade weights, calculated by authors based on NBSC statistical yearbook; 2) bilateral exchange rates between Chinese yuan and G7 currencies, directly available from IMF.

[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 OECD or world technology market: more in Dosi et al. (1990).

Figure 1: Unit labour cost of Chinese manufacturing relative to the world (proxied by G7 countries).
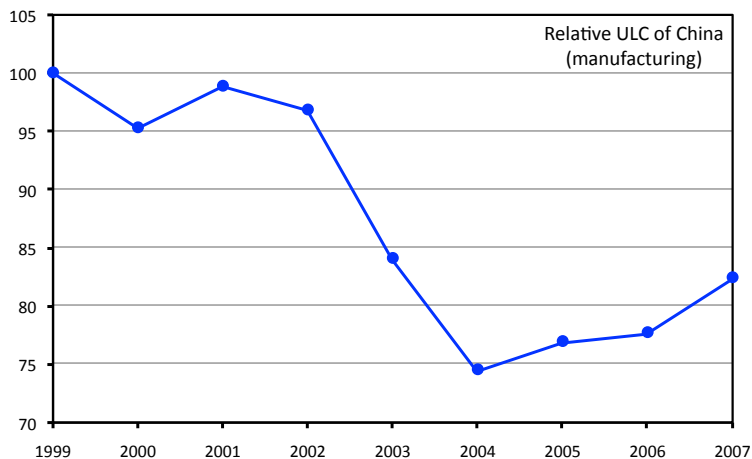
Source: Chinese firm-level dataset (Chinese unit labour cost); OECD.stat (G7 unit labour cost); China Statistical Yearbook (China-G7 trade weights); IMF (exchange rates between China and G7 countries).

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 labour* from the traditional sector served as a source of cheap labour for almost three decades of rapid capital accumulation and industrialization in China, without dramatic increase in wages (see Lewis, 1954; Lutz, 2014; and Cai and Wang, 2010 for China). 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 relative unit labour cost shows a *decreasing* trend until 2004 and kept stable/or mildly increased afterwards (see Figure 1), suggesting an increasing *cost advantages*, too, until 2004.

Second, the dramatic productivity growth and catching-up has been well documented. For example, Yu et al. (2015) estimates a 10% labour 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 and Gong, 2011 and 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 A.1). The foreign-trade multiplier played an important role during the Chinese catching-up process, with export fuelling effective demand and leading to overall increase in output and employment (see Lin and Li, 2003 and Fu and Balasubramanyam, 2005).

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]
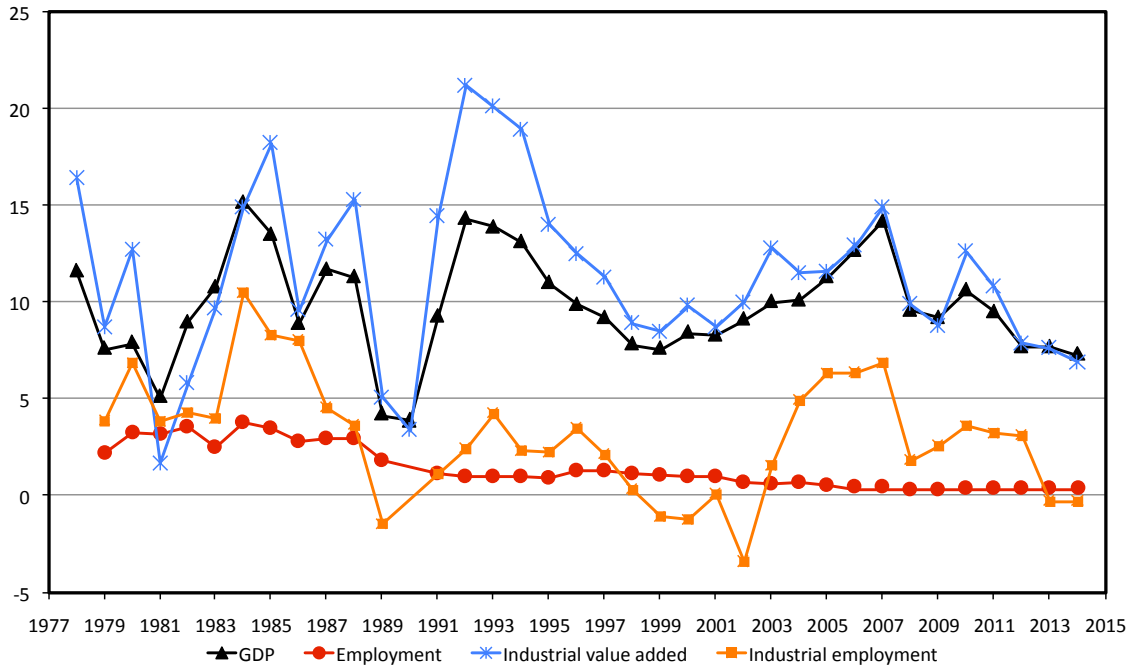
Figure 2: Growth rates of GDP, industrial value added, total employment and industrial employment. Note: The employment growth rate time series are discontinuous in 1990 as the employment statistics before 1990 are from a different data collection method. Source: National Bureau of Statistics of China.

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 (SOEs) coupled with the 'ownership transformation' process.[23] It surged to around 0.5 during 2004-07, 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.

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

[23]For the labour restructuring process associated with the ownership transformation in China, see Dong and Xu (2009) and Yu et al. (2015).
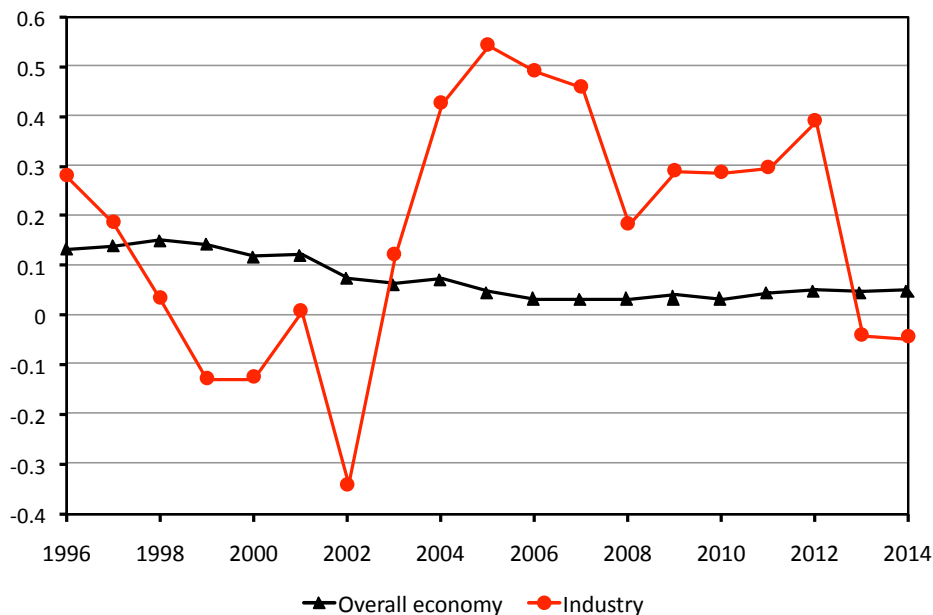
Figure 3: The elasticity of employment growth to GDP growth and industrial value added growth. Source: National Bureau of Statistics of China.

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

Source: PATSTAT (version 2014a). Year refers to patent application year. Note: if one patent corresponds to multiple assignee persons (possibly from multiple countries), we assign equal weights to each of the assignee persons.

6. Empirical results

6.1. Sectoral-level empirical estimates

First, we estimate Equation (2) for each 2-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]

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

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[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.

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

CIC	SECTOR	$\Delta\Pi_{jt}$	ΔY_{jt}	Constant	# Obs.	R2
	All manufacturing	−0.4803***	0.7743***	−0.0031	3812	0.7475
		(0.025 5)	(0.021 9)	(0.009 8)		
13	Food from agriculture products	−0.4819***	0.8164***	0.0099	135	0.8272
		(0.051 5)	(0.063 4)	(0.025 8)		
14	Food	−0.5414***	0.8692***	0.0036	171	0.8460
		(0.131 9)	(0.060 5)	(0.026 9)		
15	Beverages	−0.5135***	0.6470***	0.0418*	108	0.7605
		(0.074 2)	(0.060 6)	(0.018 6)		
16	Tobacco	−0.4539***	0.3500*	0.0379	27	0.6967
		(0.120 8)	(0.144 1)	(0.066 8)		
17	Textile	−0.7809***	0.8860***	−0.0200	180	0.8773
		(0.077 2)	(0.031 5)	(0.023 9)		
18	Textile wearing apparel etc.	−0.5273***	0.9245***	0.0653	27	0.9097
		(0.134 5)	(0.082 8)	(0.053 6)		
19	Leather etc.	−0.4610***	0.8897***	−0.0452	90	0.7785
		(0.090 1)	(0.092 4)	(0.043 7)		
20	Timber, wood, bamboo	−0.6740***	0.7005***	0.0528	72	0.8268
		(0.077 7)	(0.068 5)	(0.032 2)		
21	Furniture	−0.5555***	0.8217***	−0.0699	45	0.9198
		(0.090 1)	(0.075 3)	(0.068 4)		
22	Paper products	−0.7136***	0.4840***	0.0528*	45	0.8386
		(0.067 0)	(0.076 0)	(0.025 0)		
23	Printing, reproduction and recording media	−0.2803**	0.9117***	−0.0482	45	0.9431
		(0.106 5)	(0.055 4)	(0.031 1)		
24	Articles for culture, education, sports	−0.3238**	0.7602***	0.0362	126	0.6465
		(0.121 5)	(0.103 3)	(0.030 4)		
25	Petroleum, coking, nuclear power	−0.6094***	0.8040***	0.0759	36	0.9064
		(0.087 2)	(0.108 0)	(0.081 7)		
26	Raw chemical materials and chemical products	−0.6045***	0.8904***	−0.0208	270	0.8043
		(0.054 1)	(0.045 8)	(0.018 4)		
27	Medicines	−0.3175***	0.4989***	0.0365*	54	0.7837
		(0.094 0)	(0.064 6)	(0.018 3)		
28	Chemical fibers	−0.4152**	0.7422***	−0.0146	63	0.7234
		(0.127 0)	(0.096 3)	(0.044 7)		
29	Rubber	−0.4274***	0.6851***	−0.0323	81	0.6527
		(0.126 7)	(0.089 8)	(0.036 2)		
30	Plastics	−0.6164***	0.9718***	−0.0444	81	0.8532
		(0.074 4)	(0.086 8)	(0.025 1)		
31	Non-metallic mineral products	−0.5255***	0.7926***	−0.0150	270	0.7565
		(0.070 3)	(0.078 1)	(0.014 6)		
32	Ferrous metals	−0.3637**	0.9252***	−0.0649	36	0.8482
		(0.122 5)	(0.092 6)	(0.052 5)		
33	Non-ferrous metals	−0.6812***	1.0312***	−0.0883*	135	0.7981
		(0.097 9)	(0.075 9)	(0.038 0)		
34	Metal products	−0.4436***	0.8207***	−0.0181	162	0.7994
		(0.077 5)	(0.075 4)	(0.017 1)		
35	General purpose machinery	−0.5642***	0.7077***	−0.0278*	279	0.7863
		(0.053 2)	(0.041 4)	(0.011 7)		
36	Special purpose machinery	−0.5344***	0.8323***	−0.0530*	378	0.7739
		(0.080 4)	(0.059 8)	(0.021 1)		
37	Transport equipment	−0.2476***	0.6464***	−0.0459	207	0.7522
		(0.071 1)	(0.062 9)	(0.030 9)		
39	Electrical machinery	−0.6826***	0.8758***	−0.0012	216	0.8377
		(0.070 1)	(0.063 0)	(0.019 8)		
40	Communication equipment, computers etc.	−0.3269***	0.7512***	−0.1002**	140	0.8363
		(0.052 7)	(0.083 4)	(0.031 7)		
41	Measuring instruments etc.	−0.2524**	0.6315***	−0.0307	225	0.7109
		(0.081 7)	(0.061 7)	(0.047 5)		
42	Artwork and other manufacturing	−0.5954***	0.8637***	0.0213	108	0.8554
		(0.094 9)	(0.049 7)	(0.029 4)		

Note: OLS regression. Robust standard errors are in parenthesis. ΔN_{jt} 4-digit sectoral employment variation; $\Delta\Pi_{jt}$ 4-digit sectoral productivity growth; ΔY_{jt} 4-digit sectoral sales growth. Year dummies are included in all estimations. 2-digit sectoral dummies are included in the "all manufacturing" estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 labour-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 relative unit labour cost and world income growth. The estimates are shown in Table 5.[25] The

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[25]Here, we adopt "regression through the origin (RTO)": it implies that the dependent variable is assumed to be zero when

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

CIC	SECTOR	$\Delta\Pi_{jt}$	$\Delta EXPORT_{jt}$	Constant	# Obs.	R2
	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)		
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)		

OLS regression. Robust standard errors are in parenthesis. ΔN_{jt} 4-digit sectoral employment variation; $\Delta\Pi_{jt}$ 4-digit sectoral productivity growth; $\Delta EXPORT_{jt}$ 4-digit sectoral exports growth. Year dummies are included in all estimations. 2-digit sectoral dummies are included in the "all manufacturing" estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

effect of income elasticities dominates 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

independent variables are zeros. 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 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 1) the standard errors of the estimates of RULC are very similar in two methods; 2) the standard errors of the estimates of world income growth is much smaller in RTO than under OLS.

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

CIC	SECTOR	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R2
	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)		
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 fibres	−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)		

OLS regression without constant. Robust standard errors are in parenthesis. ΔY_{jt} 4-digit sectoral sales growth; $\Delta RULC_{jt}$ 4-digit sectoral manufacturing relative unit labour cost growth; $\Delta WorldIncome_t$ world income growth. 2-digit sectoral dummies are included in the "all manufacturing" estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

equipment and computers, electric machinery, measuring instruments, transport equipments.

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 equipments, electrical machinery, communication equipments, computers and measuring instruments.

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 as-

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

CIC	SECTOR	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	# Obs.	R2
	All manufacturing	−0.2861**	1.3538	2494	0.1185
		(0.099 1)	(0.736 9)		
13	Food from agriculture products	−0.1733	2.1071	90	0.0301
		(0.574 8)	(1.379 0)		
14	Food	−0.6468	3.1172**	112	0.1458
		(0.344 1)	(0.999 4)		
15	Beverages	−0.9427**	0.6623	72	0.0747
		(0.350 5)	(1.814 7)		
16	Tobacco	0.0087	1.7506	18	0.0596
		(0.317 3)	(2.243 8)		
17	Textile	−1.0004	3.3597***	120	0.1431
		(0.600 6)	(0.881 2)		
18	Textile wearing apparel etc.	−0.0854	2.6872***	18	0.5824
		(0.292 8)	(0.548 9)		
19	Leather etc.	−0.0731	2.5289***	60	0.1782
		(0.233 9)	(0.689 2)		
20	Timber, wood, bamboo	0.2777	5.0083***	48	0.2534
		(0.563 1)	(1.140 1)		
21	Furniture	0.1025	4.7932***	30	0.3124
		(0.577 6)	(1.292 6)		
22	Paper products	−0.5685	−0.9199	30	0.0248
		(0.619 8)	(2.670 3)		
23	Printing, reproduction and recording media	0.2193	3.3716**	30	0.1829
		(0.519 3)	(1.132 2)		
24	Articles for culture, education, sports	−0.5368***	3.2427***	84	0.3335
		(0.114 7)	(0.680 7)		
25	Petroleum, coking, nuclear power	−0.7607	2.4491	18	0.2496
		(0.595 1)	(1.520 6)		
26	Raw chemical materials and chemical products	0.2848	4.1778***	178	0.1362
		(0.297 5)	(0.739 9)		
27	Medicines	−0.1460	3.3119***	36	0.3458
		(0.243 3)	(0.699 1)		
28	Chemical fibers	−0.3386	3.3711*	42	0.1484
		(0.326 7)	(1.501 0)		
29	Rubber	−0.8314	2.6221	49	0.1148
		(0.851 4)	(1.838 0)		
30	Plastics	−0.4792**	3.8852***	54	0.5501
		(0.167 2)	(0.401 0)		
31	Non-metallic mineral products	0.3800*	3.3200***	176	0.0895
		(0.158 9)	(0.830 6)		
32	Ferrous metals	0.0872	4.4827**	24	0.3353
		(0.325 9)	(1.405 9)		
33	Non-ferrous metals	0.1449	0.5339	87	0.0038
		(0.445 5)	(2.294 5)		
34	Metal products	−0.1287	4.7038***	108	0.4462
		(0.195 4)	(0.500 4)		
35	General purpose machinery	−0.6804	4.0836***	186	0.2018
		(0.448 2)	(0.555 5)		
36	Special purpose machinery	−0.4601	5.1026***	247	0.1221
		(0.308 9)	(0.900 2)		
37	Transport equipment	−0.0706	4.8187**	126	0.0520
		(0.563 7)	(1.649 3)		
39	Electrical machinery	−0.0697	4.8119***	144	0.2286
		(0.424 3)	(0.581 6)		
40	Communication equipment, computers etc.	−1.2105**	7.4075***	93	0.5180
		(0.414 5)	(0.968 2)		
41	Measuring instruments etc.	−0.6679**	5.9891***	142	0.2106
		(0.229 3)	(1.236 4)		
42	Artwork and other manufacturing	0.3236	2.9500***	72	0.2794
		(0.233 3)	(0.570 6)		

OLS regression without constant. Robust standard errors are in parenthesis. $\Delta EXPORT_{jt}$ 4-digit sectoral exports growth; $\Delta RULC_{jt}$ 4-digit sectoral manufacturing relative unit labour cost growth; $\Delta WorldIncome_t$ world income growth. 2-digit sectoral dummies are included in the "all manufacturing" estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

signee's ones. The estimates are shown in Table 7. Together, Table 8 shows the OLS estimates for the export dynamics equation. The variation of innovativeness in Chinese manufacturing sectors seems neither contribute to sales growth nor exports growth, but, to repeat, our data refer to a stage of catching-up which by now is mostly over.

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

ISIC	SECTOR	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	$\Delta Patent_{jt}$	# Obs.	R2
	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; manuf. of luggage, handbags etc.	0.0930	3.4483^{***}	0.0495	23	0.8839
		(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 of recorded media	-0.2566	1.4286	0.0908	24	0.1662
		(0.4701)	(1.4820)	(0.1532)		
23	coke, refined petroleum products and nuclear fuel	-0.2619^{*}	3.5028^{***}	0.0623^{***}	24	0.7316
		(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 and apparatus	-0.4287^{***}	4.7009^{***}	0.0788	24	0.8815
		(0.0933)	(0.8688)	(0.0898)		
33	Medical, precision and optical instruments, watches and clocks	-0.3791^{***}	3.9597^{***}	0.0920	40	0.8413
		(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)		

OLS regression without constant. ΔY_{jt} 4-digit sectoral sales growth; $\Delta URLC_{jt}$ 4-digit sectoral relative unit labour costs 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. 2-digit sectoral dummies are included in the "all manufacturing" estimation. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 jointed 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 4-digit sector in order to ideally

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

ISIC	SECTOR	$\Delta RULC_{jt}$	$\Delta WorldIncome_t$	$\Delta Patent_{jt}$	# Obs.	R2
	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; manuf. of luggage, handbags etc.	−0.2040	2.1342***	0.0865	17	0.7077
		(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 recorded media	0.6047	1.4024	0.1534	18	0.1408
		(0.8263)	(1.9867)	(0.1511)		
23	coke, refined petroleum products and nuclear fuel	−0.6215	1.8061	0.0706*	18	0.3310
		(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 and apparatus	−0.3681**	3.8336***	0.2773***	18	0.9029
		(0.1305)	(0.9936)	(0.0834)		
33	Medical, precision and optical instruments, watches and clocks	−0.2136	1.3197	0.4252*	30	0.4150
		(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)		

OLS regression without constant. $\Delta EXPORT_{jt}$ 4-digit sectoral exports growth; $\Delta URLC_{jt}$ 4-digit sectoral relative unit labour costs 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. 2-digit sectoral dummies are included in the "all manufacturing" estimation. Robust standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 varies path-dependently with contemporaneous and past productivity and sales dynamics which reads:

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[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.

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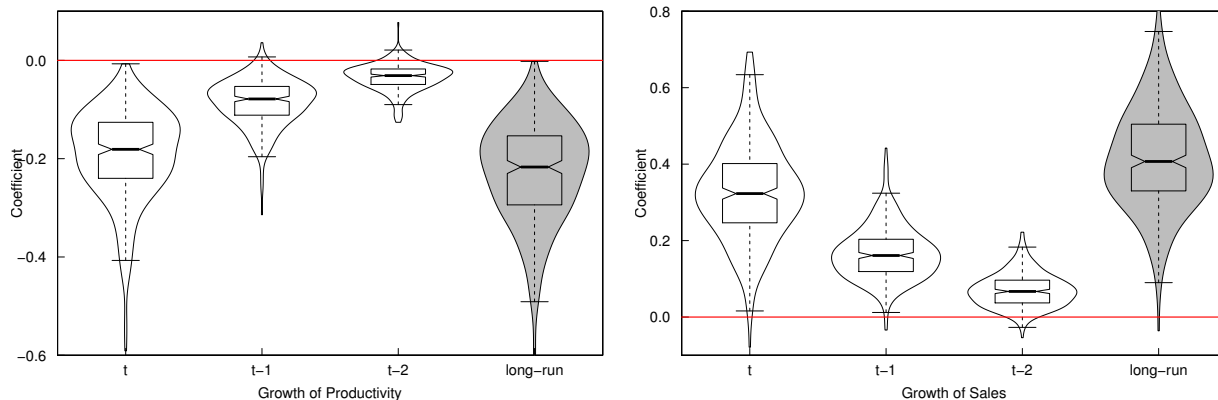
Distributions of the estimated coefficients and the long-run effects of labour productivity growth and sales growth, across 284 4-digit sectors. The shaded-violins denote the long-run effects. Only 4-digit sectors with a number of firms greater than 160.

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

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 $x \in \alpha, \beta$.

In order 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 4-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 4-digit sector.[29]

Figure 4 shows the distributions of system GMM estimates and the corresponding long-run effects over 4-digit sectors. Table 9 shows the median of the distributions of coefficient estimates. As a robustness check,

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[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~lag 6 for lag employment growth, lag 2~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~lag6.

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

	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****

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

we estimate the same model including year dummies. The results are very similar.[30] Contemporaneous and lagged productivity growth display a remarkable labour-displacing effect. Conversely, contemporaneous and lagged sales growth show 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 two consecutive years $\Delta g_{i,t} = ln(S_{i,t}M_t) - ln(S_{i,t-1}M_{t-1})$. 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 4-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,

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

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, Δm_t is the growth of market size. We control for firm's (lagged) size and age.[31]

In order to decide how many lags of dependent variable to be included into the model, we test the autoregressive structure for sales growth for each 4-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's 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 4-digit

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

[31]Here, in our baseline estimation, we do not control for year dummies, because we include the growth of market size of 4-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 et al. (2015).

Figure 5: Sales growth model: system GMM results of Equation (12) - productivity.
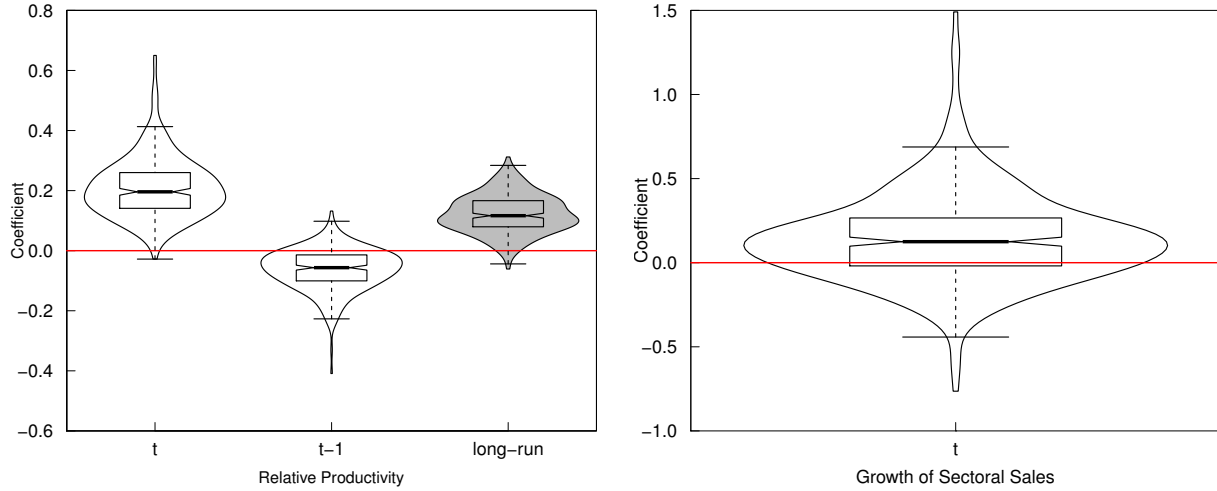
Distributions of the estimated coefficients and the long-run effects of (relative) labour productivity *level* and sectoral sales growth, across 284 4-digit sectors. The shaded-violins denote the long-run effects. Only 4-digit sectors with a number of firms greater than 160.

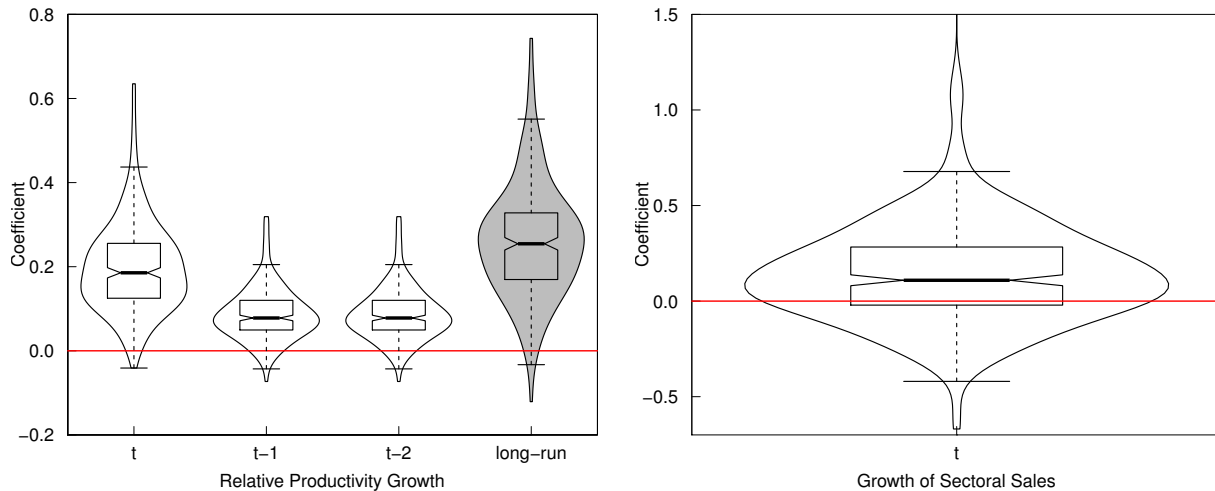Table 10: Summary statistics (median) of the distributions in Figure 5.

	t	$t-1$	Long-run
relative productivity level	0.196***	-0.057***	*0.117****
sectoral sales growth	0.125***		

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

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 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 4-digit sector. Figure 6 shows the distribution of estimates across 284 4-digit sectors, and Table 11 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.

Figure 6: Sales growth model: system GMM results of Equation (12) - productivity growth.

Distributions of the estimated coefficients of (relative) labour productivity *growth* (left) and sectoral sales growth (right), across 284 4-digit sectors. The shaded-violins denote the long-run effects. Only 4-digit sectors with a number of firms greater than 160.

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

	t	$t-1$	$t-2$	Long-run
relative productivity growth	0.186***	0.078***	0.031***	*0.255****
sectoral sales growth	0.109***			

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

6.2.4. 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

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

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

Figure 7: Employment growth model: system GMM results of Equation (13) - productivity level.
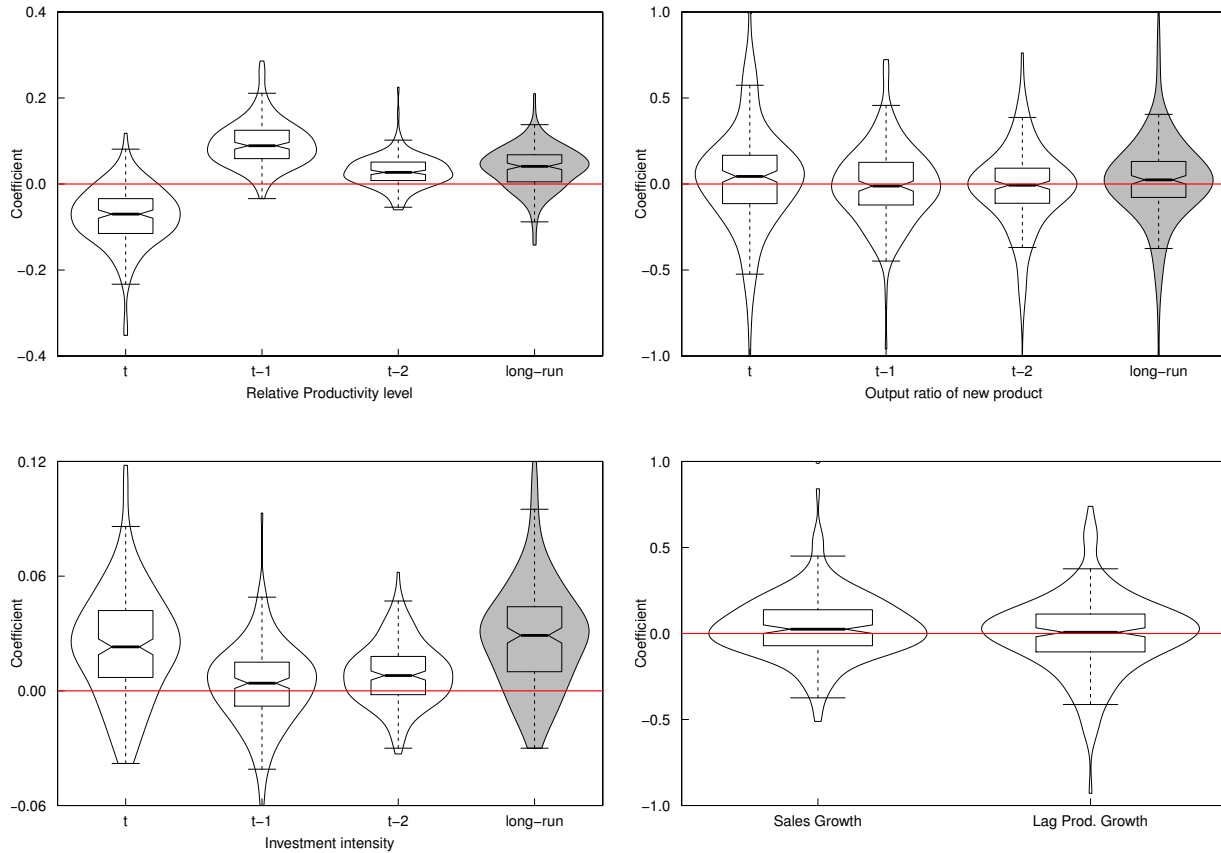
Distributions of the estimated coefficients and the long-run effects of (relative) labour productivity *level* (top left), new product ratio (top right), investment intensity (bottom left), sectoral sales growth and productivity growth (bottom right), across 177 4-digit sectors. The shaded-violins denote the long-run effects. Only 4-digit sectors with a number of firms greater than 160.

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

According to our matching results between our firm-level dataset and firm's *patenting* activities in the USPTO, 99% of Chinese patents granted in the USPTO is from the manufacturing of communication

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

	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			

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

Figure 8: Employment growth: system GMM results of Equation (13) - productivity growth.
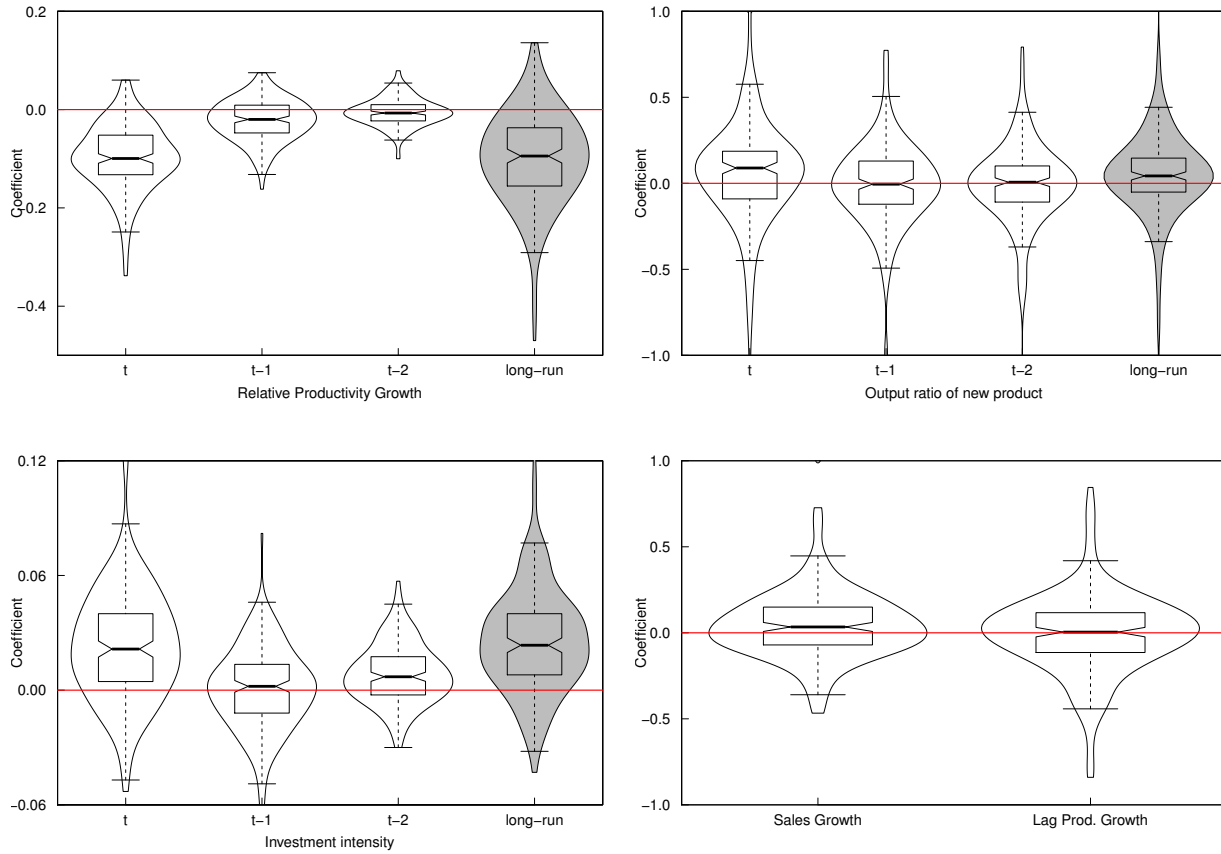
Distributions of the estimated coefficients and the long-run effects of (relative) labour productivity *growth* (top left), new product ratio (top right), investment intensity (bottom left), sectoral sales growth and productivity growth (bottom right), across 177 4-digit sectors. The shaded-violins denote the long-run effects. Only 4-digit sectors with a number of firms greater than 160.

equipments computers etc. (CIC 40) during the period 1998-2007. We further investigate the effect of patenting activities on firm's employment growth for each 4-digit sector within the broad CIC 40 sector.

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

	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			

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

(There are 16 4-digit sectors in CIC 40.) We create a time invariant dummy variable distinguishing patenting firms from the others, which equals to one if a firm has been granted a patent for at least one 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 4-digit sectors, which are the manufacturing of communication exchange equipment (CIC 4012) and semiconductor discrete devices (CIC 4052).[34]

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 are 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 paper 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.

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[34]Results are available upon request.

[35]We do not include year dummies in order to address the association between *absolute* growth of sales and *absolute* growth of productivity. As a robustness check, the estimates for models with year dummies are shown at the bottom panel of Table 14.

Figure 9: Dynamic Verdoorn-Kaldor Law: system GMM results of Equation (14).
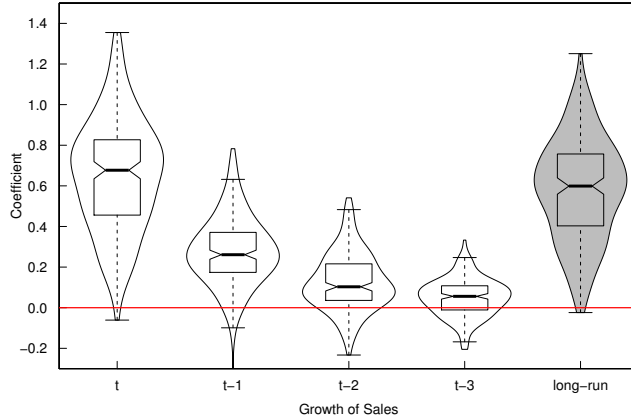
Distributions of the coefficients and the long-run effects of growth rates of sales across 193 4-digit sectors. The shaded-violins denote the distribution of long-run effects. Only 4-digit sectors with a number of firms greater than 160.

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

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

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

First, employment dynamics at the sectoral level is the joint outcome of the dynamics of labour productivity growth, which we take as a broad measure of technological progress on the one hand, and absolute competitiveness in the international markets, proxied by exports growth, on the other. The results reveal both a powerful labour-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) contributes to employment growth in the long-run, while process innovation (proxied by productivity *growth*) displays significant labour-displacement effect.[36] Firm's investment positively contributes to em-

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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.

ployment 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 labour-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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A. Table Appendix

Table A.1: Summary statistics (total) of the Chinese manufacturing firm-level dataset.

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

Source: our original firm-level dataset (only after adjustment of sectors changes between 2002/03). Note: all values are denoted in trillion RMB and employment in millions of workers. All manufacturing firms are included. Exports 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 A.2: Summary statistics (mean) of the Chinese manufacturing 4-digit sectoral-level dataset.

Year	Number of 4-digit Sectors	Employment	Sales	Labour Productivity	Exports	Wage per Employee	Employment Growth	Sales Growth	Labour Productivity Growth	Exports Growth	Growth of (nominal) wage per employee
1998	424	96711	11	36	2	7	NA	NA	NA	NA	NA
1999	423	103649	13	40	3	8	0.067	0.186	0.120	0.095	0.060
2000	424	100313	16	47	3	9	-0.030	0.125	0.141	0.247	0.126
2001	423	100470	18	53	4	10	0.010	0.136	0.126	0.114	0.086
2002	424	102602	21	61	5	11	0.043	0.178	0.141	0.152	0.077
2003	424	108984	28	71	6	12	0.075	0.242	0.153	0.287	0.098
2004	424	117450	37	89	NA	13	0.064	0.202	0.200	NA	0.139
2005	424	135751	49	93	11	15	0.160	0.303	0.089	NA	0.144
2006	424	145965	62	108	14	18	0.081	0.239	0.158	0.218	0.141
2007	424	143572	75	129	16	21	-0.025	0.158	0.178	0.059	0.189

Source: the cleaned firm-level dataset. Note: values of sales and exports are denoted in billion RMB; labour productivity and wage per employee are denoted in 1000 RMB. Labour productivity is in 1998 constant price. Growth rates re calculated as log differences of real value.

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

In order to identify whether the firms in the NBS database hold patents in the USPTO or not during 1998-2007 (according to the application filing dates), we match several databases as follows. 1) 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. 2) We get the BvD ID and NBS ID matches from the Oriana database (version 2017 January, BvD Asian-pacific regions). 3) We match NBS firm-level database with PATSTAT through the NBS ID and BvD ID. Finally, as shown in Table B.3, we get the 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 equipments 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 4-digit sectors in telecommunication manufacturing (CIC 40).

Table B.3: Number of patents in the USPTO filed by Chinese firms. Note: Years refer to the application filing year. Exclude design patents.

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]

To estimate the effect of innovativeness at *sectoral* level, we merge our 4-digit aggregated Chinese manufacturing dataset with the patent dataset (source: PATSTAT version 2014a, USPTO patents only) based on the procedures: 1) convert 4-digit Chinese Industry Classification into 4-digit ISIC (Rev3) codes; 2) match the 4-digit patent IPC code with the 4-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 4-digit ISIC sector respectively; 3) merge the above two datasets by the unique ISIC code.

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[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); 1 is from special purpose machinery (CIC 36).