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Investigating the linkages between industrial policies and M&A dynamics: Evidence from China

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ABSTRACT

Mergers and acquisitions (M&As hereafter) have been widely examined in the economic and business literature under many perspectives. However, the industry-level view, specifically the relation between industrial policies and M&A waves at the sectoral level, has remained rather unexplored. This article contributes to fill this gap by empirically investigating the relation between selective industrial policies and M&A waves at the industry level in China. Referring to the four Five Year Plans covering the period 1996–2015, we explore whether being identified as an emerging sector in these plans generates positive or negative changes in the number of M&As. We reiterate the analysis according to the different types of M&As (vertical, horizontal or conglomerate) and the different natures of the acquirer (SOEs or private). Our results suggest that policies can differentially affect M&A waves according to the type of M&A. Moreover, while private firms are more responsive to both horizontal and vertical integration in emerging sectors, SOEs are more prone to engage in vertical M&As. We discuss the possible rationales behind the different behaviors. We also draw general policy implications on strategic industrial policy and market restructuring.

1. Introduction

Mergers and acquisitions (M&As hereafter) have been widely studied in the economic literature. Many scholars have focused on firm-level advantages or disadvantages originating from M&As (Burt & Limmack, 2003; Schweiger & Very, 2003; Fortune, 2005; Angwin, 2007; Kwon, Lee, & D. H., 2018; Harrison, Hitt, Hoskisson, & Ireland, 1991, and so on), and other researchers have focused on the role of managers and other stakeholders in promoting or hampering biddings (Baumol, 1959; Anderson, Havila, & Nilsson, 2013; and many more).

The role of M&As in transforming the structure of a sector, however, has been less explored. In particular, there is little empirical evidence on the linkages between industrial policies and M&A waves. Nevertheless, the topic is relevant in particular in the context of emerging countries with strong industrial policy apparatuses, since the possibility of driving M&As can become a powerful means to promoting structural change.

We aim to fill this gap by studying the case of China. Since the introduction of the open door policy in 1979, China has used selective

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industrial policies to promote the development of specific sectors, territories and technologies (Biggeri, 2017; Di Tommaso, Rubini, & Barbieri, 2013; Jiang & Li, 2010; Xiang & Zhang, 2013). Selective policies targeting sectors in particular have nurtured the growth of specific productions, technologies, national champions, etc. (Barbieri, Di Tommaso, Tassinari, & Marozzi, 2019; Chu, 2011; Nolan, 2001; among others), and their importance is currently acknowledged outside China (Andreoni, 2017).

More generally, Chinese policymakers have been pushing a structural change of their economy, identifying specific sectors within the Five Year Plans (FYPs hereafter), China's main policy documents. Chinese policymakers themselves recognize the role of M&As in transforming the features of firms and markets, up to the point that merger waves are explicitly encouraged in FYPs for particularly relevant sectors.

Our paper explores whether the identification of sectors that are particularly relevant in the FYP works as an incentive for economic actors to engage in M&As. To do so, we empirically explore the linkage between Chinese sectoral selective policies in the FYP and M&A waves at the industry level, with particular reference to emerging sectors. Using an original database compiled from several sources, we discriminate among the various forms of mergers (vertical/horizontal/conglomerate) and ownership of the acquirer (SOEs/private) to understand whether sectoral identification is able to influence M&A trends. Our main intuition is as follows: the selection of specific sectors in the FYP has already been shown to produce effects on economic performance (Wu, Zhu, & Groenewold, 2019). This happens because, after selective identification in the FYP, a whole range of encouraging policies follows (Kenderdine, 2017; Sun, Wu, & Liu, 2014; Zhao, Li, Zhao, & Ma, 2019). In the case of emerging sectors, policymakers use this scheme to promote a systemic shift of the economy towards frontier-technology productions (Chen, 2015; Prud'homme, 2016; Yang, 2015). In our view, therefore, the selective identification in the FYP acts as a signal that in the forthcoming years, these sectors will be at the core of the structural transformation of the economy. Although single actors do not know, since the beginning, what specific measures will be taken to promote these sectors, the sole identification of emerging sectors may, henceforth, be able to spread positive expectations in relation to those sectors and produce a reorganization in the markets via M&As.

To the best of our knowledge, ours is one of the first papers shedding light on the potential signaling effects of policies towards M&As and the sectoral structural change they trigger. In this regard, our contribution is explorative and wishes to open future lines of research. We try to address the causal link between being identified as an emerging sector and the number of M&As that are realized during the FYP period via a three-step instrumental variable approach (Adams, Almeida, & Ferreira, 2009; Wooldridge, 2010), using as an instrument a proxy for the technology level of the sectors in OECD countries.

The paper is structured as follows: the next section reviews the relevant literature on M&As. Section 3 focuses on Chinese selective policies in the FYPs and the distinction between pillar and emerging sectors, concluding with three empirical questions. The data and methodology description (section 4) and the empirical investigation (5) follow. Section 6 concludes with further discussion on the results and policy-oriented final remarks.

2. Literature review

2.1. Mergers and acquisitions: Types and determinants

Largely, the literature has studied M&As from the microeconomic or firm-level perspective, with fewer contributions using a meso-macroeconomic (country or industry) focus. For our purposes, we are mainly interested in the latter, although some implications on microdeterminants are useful to understand the phenomenon and to build our empirical investigation.

At the industry level, M&As have an important role in modifying the structure of the market and its governance mechanisms (Holmstrom & Kaplan, 2001). In general, M&As are a powerful means for asset reallocation within and across industries, and they serve either the expansion or the contraction of an industry, according to the conditions of the sector (Andrade & Stafford, 2004). On the one hand, they can produce an increase in the asset base at the firm and sector levels, particularly in periods of prospective expansion of the sector. On the other hand, M&As have been used to consolidate sectors, rationalize assets and improve their efficiency, particularly in periods of restructuring and excessive capacity. More generally, M&As are a vehicle for market evolution, allowing sectors to adapt to shocks and changes in the economic environment via resource reconfiguration (Fortune, 2005). Consistent with their structural function, M&As have been observed to cluster asymmetrically across industries (Szücs, 2016; Yaghoubi, Yaghoubi, Locke, & Gibb, 2016) and to respond to industry-level or economy-wide shocks (Andrade & Stafford, 2004; Harford, 2005). Additionally, industry factors, such as sales concentration, scale efficiency and competition, seem to assume great importance in determining the specific advantages and conditions that companies can exploit with M&As, and therefore, they are capable of influencing success in terms of postmerger firm-level gains and value. Finally, M&As tend to cluster across related industries, acting as a mechanism of asset reallocation along the production chain (Huyghebaert & Luypaert, 2013; Szücs, 2016).

Concerning firm-level determinants, M&As are used to generate scale and scope economies and to acquire various forms of assets - financial and physical capital, managerial and knowledge capabilities, technology, and market share (Angwin, 2007; Burt & Limmack, 2003; Fortune, 2005; Harrison et al., 1991; Kwon et al., 2018; Schweiger & Very, 2003). In addition, M&As are regarded as strongly strategic activities that economic actors implement to change, either directly or indirectly, competition, market power, and bargaining leverage along the value chains (Adams, Johnson, & Pilloff, 2009; Anderson et al., 2013; Angwin, 2007; among others). Although the two studies have seldom crossed their paths, the asset reallocation produced by M&As can be interpreted as a source of structural change (Andreoni & Scazzieri, 2014; Cardinale, 2018; Cardinale, Coffman, & Scazzieri, 2017; Cardinale & Scazzieri, 2019). In fact, M&As change the structural configurations of sectors and markets and impact the relations and interdependences among actors at various levels.

Both empirical and theoretical studies have highlighted that the strategic advantages and synergies that can be activated through

M&As, as well as their impacts on industrial competitiveness and structure, are different according to the typologies of the M&As (Anderson et al., 2013; Gugler, Mueller, Yurtoglu, & Zulehner, 2003). One of the most important distinctions lies in the features of acquiring versus targeting firms (Barbieri, Huang, Pi, & Tassinari, 2017; James & Wier, 1987). Following their differences in terms of sectors and position along the value chain, the literature usually distinguishes among horizontal, vertical and conglomerate M&As.[1]

Horizontal M&As are widely studied and are those for which industry-level components appear to be more relevant (Huyghebaert & Luypaert, 2013). They are regarded to generate the most important increase in sectoral efficiency and R&D, but they are those causing more problems in terms of the concentration of market power, even stronger in the case of market contraction (Adams et al., 2009; Kim & Singal, 1993; Sapienza, 2002; Schweiger & Very, 2003; Anderson et al., 2013; Barbieri et al., 2017).

The rationale behind vertical integration is different and related to the change in the supplier-customer relationship (Anderson et al., 2013). With vertical M&As, the acquirer aims, among others, to increase the value added produced internally, to reduce production costs, to acquire new technology, and to gain larger control over production phases (Milliou, 2004; Schweiger & Very, 2003; Barbieri et al., 2017). In turn, vertical integration can directly or indirectly affect competition and markets, as it can increase the market power of the newly integrated firm and can modify the relationships with previous costumers of the acquired firm (Buehler & Schmutzler, 2008). In addition, a consolidated literature on transaction costs (Coase, 1937; Williamson, 1979; to cite a few) interprets vertical M&As as a way for market actors to avoid transactions in markets when information asymmetries are high and therefore, uncertainty increases (Williamson, 1986; Whinston, 2003; Levy, 1985; Frank & Henderson, 1992). Since vertical integration and subsequent internal coordination come at some costs, firms integrate vertically when transaction costs outweigh internal coordination costs (Levy, 1985).

Finally, conglomerate M&As are considered a residual case used by firms to expand in new business lines. Strategically, these operations allow firms to employ overcapacity and to acquire new managerial and technological assets (Burt & Limmack, 2003; Schweiger & Very, 2003; Williamson, 1986), but they may generate problems for postmerger performance and sectoral competitiveness, given possible significant value losses due to diversification (Berger & Ofek, 1995; Lang & Stulz, 1994). This can be due to cross-subsidization of poor-performing segments, discretionary increase in resources to take underperforming investments, and agency problems, including misalignment among managerial branches (Scharfstein & Stein, 2000; Berger & Ofek, 1995; Lang & Stulz, 1994; Jensen, 1986; to cite a few). However, these dynamics appear to be limited to specific periods in the history of M&As, while in other historical times, diversified firms via conglomerate M&As show positive performances (Klein, 2001).

All these differences in terms of determinants, rationales, and implications highlight that the decisions to engage in M&As and their effects differ according to the type of operation. This makes a strong case for discriminating M&A types when analyzing the possible effects of policy signaling.

2.2. Mergers and acquisitions: Policies and firm behaviors

From the point of view of policies, M&As have historically grabbed attention as a tool to change the competitive dynamics in a market. Most policies had to manage the trade-off between gains in efficiency generated by sector consolidation and welfare losses associated with market power concentration (Anderson et al., 2013; Chen, Jiang, & Weng, 2020; James & Wier, 1987). Henceforth, whether public actors promote or hamper structural changes induced by M&As mostly depends on their political orientation on M&As. It also follows that choosing to impose strict (slack) antitrust regulations and enforcement works as a signal to economic actors to decrease (increase) actions aimed at changing current market structures (Di Tommaso & Tassinari, 2017; Tassinari, 2019). In the context of the Chinese economy, in particular, M&As have been used as a tool for restructuring SOEs and the state sectors by introducing mixed ownership to increase SOE efficiency and innovativeness (Zhang, Yu, & Chen, 2020). From the end of the 1990s to mid-2007, the “Grasp the Large, Let Go of the Small” policy favored the shutting down of smaller companies and, above all, the formation of large state-owned companies via M&As. This, in turn, has translated into a reduction in the number of companies owned by local and central governments and into a substantial improvement in the contribution of SOEs to productivity growth (Hsieh & Zheng, 2015; see also Petti, Prota, & Rubini, 2016; Lin, Lu, Zhang, & Zheng, 2020).

Public policies can directly and indirectly —as well as intentionally or unintentionally— influence M&As. The scope and types of measures interacting with M&A realizations and value are wide. They range from fiscal and monetary initiatives aimed at modifying the cost of capital and credit availability (Adra, 2015) to regulations lowering transaction costs in the process of M&As (Coates IV, 2018) to tax, investment and trade policies affecting M&As as a side effect (Harris & O’Brien, 2018).

Political connections and/or the vicinity of firms to public actors have a strong mediating role in the extent to which policy activity impacts M&A success and performance. This is because political connections are believed to affect access to credit, preferential fiscal measures and, in general, the overall gains obtained from public-policy actions. These aspects have been largely explored in China (Anderson, Chi, & Wang, 2017; Kam, Citron, & Muradoglu, 2008; Su, Zhang, & Zhang, 2013; Yang & Zhang, 2015), and the evidence strongly suggests that the firms’ diversity in terms of political connection and nature of ownership—whether SOEs or private—is to be taken into account when looking at the relationship between policies and M&As.

As far as China is concerned, an additional channel for policy interaction with M&A waves comes from the sector selectivity of industrial policy (Chen et al., 2020). Industrial policy initiatives in China include a wide series of measures, such as taxes, subsidies,

[1] Horizontal M&As take place among competing firms, operating in the same sector and in the same stage of the production process. Vertical M&As involve firms in the same sector but in different stages of the production process (supplier-customer), while conglomerate M&As take place among firms operating in different sectors.

fiscal, land and human resource incentives, locally targeted programs to promote selected sectors, or to restrict resource flows into/out of those sectors (Liu, 2015; Sun et al., 2014). In this regard, they can influence M&As – and specific types of M&As – in at least three ways. First, industrial policies can reallocate bank credit to the selected sector, lowering the cost of financing for firms. This makes greenfield and brownfield investments more attractive for firms because their cost relative to other sectors will be lower. Second, the implementation of selective expansive industrial policies generates sectoral-unbalanced advantages in terms of subsidies and facilitations. This stimulates firms aiming at opportunistically exploiting policy advantages to enter these sectors via conglomerate M&As (Yang, 2013; Bi, Zhang, & Li, 2015; Hua, Zhou, Zhang, & Wang, 2020). In this case, the effects in terms of welfare and sectoral performance are disputable (Xiao & Wang, 2014; Yu & Y. Lv Y., 2015) and can even lead to prolonged dependence of firms upon policy subsidies. As a third channel, Chinese industrial policies generally emphasize the firms' size growth to increase investment efficiency and scale advantages, and consequently, they provide greater facilitation for large firms (Jiang & Li, 2010; Liu, 2015). This emphasis on size may particularly stimulate aggregation via horizontal M&As.

Signaling effects of policies on individuals' expectations have been studied for monetary policies (Melosi, 2017; Montes, Oliveira, Curi, & Nicolay, 2016), as well as for public procurements and innovation policies (Qu & Li, 2019). However, selective industrial policies too can have a strong signaling effect on economic actors. It has been observed, for instance, that firms within selected sectors are more likely to access debt financing and to have a larger scale of investment than those outside selected sectors (He, Yin, & Mao, 2016). For the firm- and industry-level efficiency of these investments, the debate among Chinese scholars is still open. Some papers have found evidence of a positive association between industrial-policy measures and firm-investment scale and efficiency (He et al., 2016). Other studies have highlighted that, while more supported in terms of access to credit and financial resources, firms in selected sectors see a decrease in investment efficiency (Tang & Luo, 2016), with consequential over-investment and excess production capacity at the sector level (Yang, 2013; Jiang, Geng, Lu, & Li, 2012; and so on). From this perspective, policies stimulating M&As and industrial rationalization may also counterbalance overcapacity and channel proper investment growth.

3. China's selective industrial policy and the five-year plans

With the launch of the Open Door Policy, China's economic structure has gradually shifted away from a centrally planned economy. In this respect, rather than going towards an open market economy, the national system has moved towards capitalism with Chinese characteristics or a socialist market system, in which Chinese governments have been active in designing and driving the structural changes of their economy. The selectivity of policies is a constitutive part of this framework (Di Tommaso et al., 2013; Barbieri, Pollio, & Prota, 2020; Nolan, 2001; Zheng, Barbieri, Di Tommaso, & Zhang, 2016).

From this perspective, since the 1980s, the Chinese government has intensively produced a large number of industrial-policy measures, forming a complex structure in which the same instruments have been adapted to reach different shifting objectives (Barbieri, Di Tommaso, Pollio, & Rubini, 2020; Di Tommaso et al., 2013; Jiang & Li, 2010; Xiang & Zhang, 2013). After the global crisis in 2008, these efforts became more systematic (Jiang & Li, 2010), and the State Council of Central Government alone issued more than one hundred industrial-policy measures devoted to manufacturing. These measures are characterized by direct interventions in micro markets and the selection of sectors, technologies and products to be promoted. Additionally, they are oriented to support large firms and to support the increase in average firm size.[2] This evidence underlines the complexity of industrial policymaking in China, as reflected by a rich debate among Chinese scholars on the efficacy of policy intervention, its potential inefficiencies and the possible mechanisms to mitigate its failures (Shu, 2013; Zhao, 2016; Wang, Sun, & Niu, 2014; and more).

Among the measures defining the governmental industrial-policy strategy, the FYPs remain the primary programmatic documents (Heilmann & Melton, 2013; Hu, 2013; Wu et al., 2019), through which Chinese leadership expresses its long-term economic vision and identifies which sectors and firms (mainly SOEs) should channel economic upgrading in the mid-term.[3]

Even though they currently aim to provide guidelines, rather than defining binding targets, FYPs always give precise indications on industries that are to be considered strategic (Barbieri, Di Tommaso, Tassinari, & Marozzi, 2019; Wu et al., 2019). Specifically, FYPs define sectors in two ways: as *pillar industries* or as *strategic emerging* (emerging hereafter) *industries*. While pillar industries are major well-established sectors, with a pivotal role in supporting the current economic structure, emerging industries are those with the largest innovative and systemic upgrading potential, as well as those that are expected to contribute the most in the future to GDP growth (Chen, 2015; Sun et al., 2014). Policymakers identify emerging sectors as those that have—in the moment where they are

[2] As an additional feature, Chinese selective IPs have a multilevel nature; that is, policy measures are not only issued and implemented by the State Council of Central Government and by Central Government departments. They also have specific levels of implementation in provincial and city level governments, which contributes to depict a complex industrial-policy framework with multiple, and sometimes conflicting, levels of implementation (Jiang & Li, 2010; Liu, 2015; Xiang & Zhang, 2013).

[3] Although the formulation process of the FYP has been maintained to be a "black box" in general, few new contributions managed to trace the formation approach of China's Five Year Plan over the last six decades, which opens parts of the box. Across the six decades of the leadership of the Communist party, this tool has changed in terms of formulation and approach. While in the first plans, it was more linked to a top-down dirigistic approach; from the 7th plan (1986–1990) onwards, it has taken a more consultative stance, particularly from the 10th plan (2001–2005) onwards (Hu, 2013); and currently, it is based on a continuative process of monitoring, revising and brainstorming by a plurality of actors. Among the steps of formation, setting up the drafting team and forming the National Planning Committee of Experts are of particular importance. This decision-making process currently involves surveys, investigations, field studies and consultations with representatives from academic communities and social actors (Heilmann & Melton, 2013; Hu, 2013) and, since the 13th FYP, from entrepreneurs as well.

Table 1
Pillar and emerging sectors in the 9th to 12th five-year plan.

Sector definition	IX Plan (1996–2000)	X Plan (2001–2005)	XI Plan (2006–2010)	XII Plan (2011–2015)
Agricultural and Sideline Food Processing				P
Textile Industry	E	P	P	E
Textiles and Clothing, Apparel Industry		P		
Petroleum Processing, Coking and Nuclear Fuel Processing				E
Raw Chemical Material & Chemical Products	E	P	E/P	E
Medical and Pharmaceutical Products		E	E	E/P
Chemical Fiber			E/P	E
Nonmetal Mineral Products	E	P	E/P	P
Ferrous Metal Smelting and Rolling Processing Industry				P
Nonferrous Metal Smelting and Rolling Processing Industry		P	P	P
Metal Products			E	
Ordinary Machinery Manufacturing		P	P	P
Special Equipment Manufacturing		P	P	P
Automobile Manufacturing Industry		P	P	P
Railways, Shipbuilding, Aerospace and Other Transportation Equipment Manufacturing Industry	P	P	P	E
Electrical Machinery and Equipment Manufacturing		P	P	P
Computers, Communications and Other Electronic Equipment Manufacturing Industry	E/P	P	E	E/P
Instrument Manufacturing		P	E	
Electricity and Heating Production and Supply Industry			P	E
Water Production and Supply				E
Total number of pillar sectors	*2*	*12*	*11*	*10*
Total number of emerging sectors	*4*	*1*	*7*	*9*

Source: authors' compilation.

identified—a relatively small role in the domestic economy. Nonetheless, they are seen as those that, given global-market dynamics, have promising growth potential and, above all, are characterized by high technology and high knowledge endowments.

The identification of these sectors has acquired particular relevance after the launch of the National Plan on indigenous innovation in 2006 (State Council, 2006) since these sectors have been more clearly identified as those with the highest potential to produce a general shift towards a knowledge-intensive and innovation-driven system (Yang, 2015; Zhao et al., 2019). Since then, selective policy interventions have polarized around emerging industries, with further dedicated policy plans for their development (State Council, 2010a) and structuring an entire "policy system" (Sun et al., 2014). The dedicated measures are wide in number and scope, ranging from locally targeted incentives to provincial- and city-level specific specialization initiatives, to product/sector lists that are encouraged/forbidden to foreign entries, and to incentives to individual actors in the forms of tax exemptions, subsidies and other similar incentives (Sun et al., 2014; Kenderdine, 2017; Zhao et al., 2019; Zhong, Meng, Zhu, & Wang, 2020). Emerging industries are currently considered a core part of China's national catch-up strategy (Prud'homme, 2016), and the techno-industrial policies that are attached to them act as a policy transmission method for the coordination of Chinese economic transformation (Kenderdine, 2017). In other words, policymakers consider emerging sectors as able to drive a systemic transition towards high-growth, high-value added and frontier-technology productions (Chen, 2015; Prud'homme, 2016; Yang, 2015).

Central and local governments specifically target firms in those sectors with facilitations and subsidies while being particularly relaxed on entry market regulations to facilitate their expansion (Zhu & Liu, 2011). As a consequence, Chinese scholars have noted that emerging sectors attract firms from outside, also via M&As, and that new entrants' moral hazard and firms' adverse-selection phenomena may arise as a consequence (Hong & Zhang, 2015; Lu & Yu, 2012),

Table 1 represents the identification of pillar and strategic emerging sectors in the four FYPs from 1996 to 2015.[4]

After FYPs are issued, sector-specific plans and execution documents at the national and local levels usually follow, particularly for emerging sectors (Barbieri et al., 2017; Heilmann & Melton, 2013; Pollio, Barbieri, Rubini, & Di Tommaso, 2016). These documents include precise targets, objectives and instruments, as well as general indications for private and public firms. Additional specific measures provide impulses for sectoral market structural change via rationalization and M&As. This is the case for the "Opinion on Corporate Mergers and Acquisitions" (OCMA) issued by the State Council in October 2010 and revised in 2012, which includes a set of direct and indirect measures to accrue sectoral rationalization via M&As (Chen et al., 2020; State Council, 2010b). In identifying the sectors that are affected by these measures, the OCMA conforms to the list of emerging products and pillar sectors defined in the FYPs.

The joint discussion of the literature review and the experience of Chinese selective planning allows us to formulate three empirical research questions (ERQs):

ERQ1) Can M&A waves be potentially affected by five-year plan sector identification as emerging?

ERQ2) Does the relationship between policies and M&A waves change according to the type of M&A under analysis – whether

[4] The table only includes information for the sectors that are included in the dataset that we use for the present study. It is therefore, not exhaustive of all the pillar and emerging sectors as identified by the plans.

Table 2
Summary statistics of the dependent variables.

Variable	Obs.	Mean	S. D.	Min	Max	Description
I. Main analysis: M&A by target sector						
$MA\_TOT_{i,t}$	495	4.03	11.38	0	76	Number of total M&A towards sector i in time t
$MA\_HOR_{i,t}$	495	0.97	2.93	0	25	Number of horizontal M&A towards sector i in time t
$MA\_VER_{i,t}$	495	1.86	6.11	0	64	Number of vertical M&A towards sector i in time t
$MA\_CONGL_{i,t}$	495	1.03	3.22	0	38	Number of conglomerate M&A towards sector i in time t
II. M&A by target sector: SOEs vs private acquirer						
$MA\_TOT\_pub_{i,t}$	495	0.95	2.76	0	20	Number of total M&A by SOEs towards sector i in time t
$MA\_VER\_pub_{i,t}$	495	0.49	1.55	0	11	Number of vertical M&A by SOEs towards sector i in time t
$MA\_HOR\_pub_{i,t}$	495	0.27	1.13	0	11	Number of horizontal M&A by SOEs towards sector i in time t
$MA\_CONGL\_pub_{i,t}$	495	0.15	0.58	0	5	Number of conglomerate M&A by SOEs towards sector i in time t
$MA\_TOT\_priv_{i,t}$	495	2.13	6.74	0	52	Number of total M&A by private firms towards sector i in time t
$MA\_HOR\_priv_{i,t}$	495	0.46	1.61	0	16	Number of horizontal M&A by private firms towards sector i in time t
$MA\_VER\_priv_{i,t}$	495	1.10	4.14	0	48	Number of vertical M&A by private firms towards sector i in time t
$MA\_CONGL\_priv_{i,t}$	495	0.47	1.99	0	30	Number of conglomerate M&A by private firms towards sector i in time t

Source: authors' compilation.

horizontal, vertical or conglomerate?

ERQ3) Does this relationship depend on the nature of the acquirer – whether SOE or private?

4. Data and methodology

4.1. Data, variables and baseline model

Our analysis is based on an originally compiled dataset coming from the merging of different sources[5] and covering 33 two-digit industrial sectors from 1999 to 2013.[6] It includes data on the number of M&As – as total and by type – of each sector *i* in year *t*, various information related to industrial activities and performances, and whether in year *t* sector *i* is classified as pillar and/or strategic and emerging by the corresponding FYP.

Our final dataset includes all 1995 M&A events that occurred between 1999 and 2013 for which the target company belongs to the industrial sector.[7]

For the methodology, we first extensively describe the data to give a proper representation of the phenomenon of M&As in China. To test our research questions, we then proceed with the econometric analysis. We run different models, which vary according to the type of dependent variables that are considered (reported in Table 2).

We first run a general analysis taking into account four dependent variables for each sector *i* at time *t*: total M&A events, vertical M&A events, horizontal M&A events and conglomerate M&A events.

Second, we investigate whether significant differences exist if the acquirer is an SOE or a private firm. In this case, for each sector *i* at time *t*, we analyze two groups of dependent variables. The first represents the M&As realized by SOEs – total and by type – while the

[5] For the data on M&A, we use the Zero2IPO Database System (China). Zero2IPO Database covers all events of Chinese M&A in all sectors between 1998 and 2013. Among other information, Zero2IPO includes the acquirer company's name, the type of ownership and sector, as well as the target company name and sector and the type of M&A – whether vertical, horizontal or conglomerate. Data about industrial performances and indicators are taken from China Data Online, which gathers information on industrial performances from official Chinese sources and yearbooks from 1999 to 2015. Finally, to identify whether and how each industry is mentioned in every five-year plan, we ran a Structural Content Analysis on the 9th, 10th, 11th and 12th Five-year Plans for National Economic and Social Development of The People's Republic of China, which covers the time span 1996–2015.

[6] The dataset includes all industrial sectors as classified by the Chinese national statistics according to the Chinese Industrial Statistic Classification issued in 2011 (GB/T 4754–2011). These include (I) extraction and mining activities, (II) manufacturing and (III) utilities production, supply and management. The sector broadly corresponds to Sections B to E of the International Standard Classification of All Economic Activities (ISIC). In the Chinese classification, this range corresponds to a total of 41 two-digit sectors, from which we have excluded seven sectors (6 – coal mining and dressing, 7 – petroleum and natural gas extraction, 11 – mining activities, 12 – other mining industries, 29 – rubber and plastic products, 41 – other manufacturing, 42 – waste treatment, disposal and recovery and 43 - repair of fabricated metal products, machinery and equipment). Our analysis rests, therefore, on 33 two-digit sectors. Since the Industrial Classification changed twice during the period under analysis, in 2002 and 2002, we double-checked and reclassified the industrial data and the M&A data to ensure panel coherence.

[7] The use of sector-level data is justified both by the research aim of this paper – which is focused on the structural change of markets at the sectoral level rather than on firm-level performance – and by robustness and reliability issues that are related to the use of firm-level data; in particular, when observing a phenomenon across various years (see, among others, Brandt, Van Biesebroeck, & Zhang, 2014; Wu et al., 2019).

Table 3
Summary statistics for the variables of interest and the controls.

	Obs	Mean	S.D.	Min	Max	Description	Source
Variables of interest							
Emerging	495	0.15	0.36	0	1	Whether the sector is emerging or not (includes both-pillar-and-emerging sectors)	Authors' elaboration on the 9th, 10th, 11th and 12th FYP (1996–2015)
Controls							
Pillar (only)	495	0.25	0.43	0	1	Whether the sector is a pillar or not (excludes both-pillar-and-emerging sectors)	Authors' elaboration on the 9th, 10th, 11th and 12th FYP (1996–2015)
$ROA_{i,t}$	495	26.86	22.43	−9.42	101.83	Avg. Ratio of profits to total assets in the sector	China Data Online
$FIRMS_{i,t}$	495	6.59	6.23	0.08	30.05	Total number of firms in the sector (thousands)	
$LOSS\_FIRMS\_RATIO_{i,t}$	495	1.06	8.76	0.00	195.38	Ratio of loss firms to total firms in the sector	
$DEBT\_RATIO_{i,t}$	495	56.47	7.70	23.53	76.18	Ratio of total debts to total assets	
$FIRMS\_SIZE_{i,t}$	495	31.75	112.17	0.00	787.89	Avg. number of employees per firm in the sector (thousands)	
$SOE\_RATE_{i,t}$	495	14.37	19.60	0.01	92.35	Percentage of SOEs on total firms	
$PROD\_GROWTH_{i,t}$	396	0.16	0.24	−0.49	0.74	Average growth of output in the previous two years	
$Cum\_MA\_y3_{i,t-1}$	495	8.81	26.36	0	197	3-years cumulated total M&A	Zero2IPO
$Cum\_MA\_y5_{i,t-1}$	495	10.02	29.92	0	229	5-years cumulated total M&A	
$Cum\_MA\_y7_{i,t-1}$	495	10.27	30.60	0	236	7-years cumulated total M&A	
$OCMA_{i,t}$	495	0.04	0.19	0	1	Whether the sector was targeted by the "Opinion on Corporate Mergers and Acquisition" measure	Authors' elaboration on State Council (2010b) and Chen et al., 2020
Instrumental variable							
$RD\_OECD_{i,t}$	390	0.04	0.07	0.00	0.39	Average ratio of RD employees on total employees in selected OECD countries in the five years preceding the issue of the FYP in force	Authors' elaboration on OECD STAN-SBDS databases

Source: authors' compilation.

second includes the operations carried out by private firms.

Our aim is to assess whether being defined as emerging in the FYPs has any potential effect on M&A events. $Emerging_{i,t}$ is a dummy variable that takes the value 1 if sector i in year t is an emerging sector, as identified by the FYP in force.[8]

We also include various controls. First, we control if the sectors that are not identified as emerging are pillars ($Pillar_{i,t}$) to isolate other possible plan effects related to those sectors that are considered more mature. Then, we add controls for the structure and performance of the sector. To use a proxy for the profitability of the sector and its performance, which may influence its attractiveness to new entries via M&As (Andrade & Stafford, 2004; Szücs, 2016), we add the return on assets at time t ($ROA_{i,t}$), the debt ratio ($DEBT\_RATIO_{i,t}$) and the ratio of loss-making firms at time t ($LOSS\_FIRMS\_RATIO_{i,t}$), which also controls for asset-stripping motivations (Angwin, 2007; Chang, 2008). The literature has also found a reciprocal influence between M&A gains and hence M&A motivations and the existing industry structure and concentration (Shahrur, 2005; Lang & Stulz, 1994; and so on). Since our database lacks specific concentration measures,[9] we use as a proxy for this aspect the number of firms operating in the sector ($FIRMS_{i,t}$) and the average number of employees per firm ($FIRMS\_SIZE_{i,t}$). In terms of the structure of the sector, another factor potentially relevant in the Chinese case in influencing market dynamics is the presence of SOEs; therefore, we include the percentage of SOEs on total firms above a designated size ($SOEs\_RATE_{i,t}$). Finally, to add more information on market dynamics and sector life-cycle (Anthony & Ramesh, 1992; Yan & Zhao, 2010), we use the production growth rate of the previous two years ($PROD\_GROWTH_{i,t}$). To add information on changes in the sector generated by previous M&A waves, we include the five-year lagged cumulated number of total M&A events ($Cum\_MA\_y5_{i,t-1}$).[10] Furthermore, M&As have also been observed to cluster in time waves (Andrade & Stafford, 2004); therefore, we added lagged M&A events. To measure regulatory and technological shocks more precisely (Harford, 2005; Holmstrom & Kaplan, 2001), we consider the role of each of the FYPs. The FYPs that we analyze include different sectoral and overall economic prescriptions and have different approaches and attitudes towards rationalization and M&A sectors (see section 3). To control for this, we include a set of dummies, each identifying one FYP period. In addition, referring to the OCMA policy (see section 3), which explicitly promotes M&As

8 The "emerging" case also includes those sectors that are identified both as Pillar and as Emerging. This is because it is sensible to think that, while pillar sectors are well-established sectors, which are more likely to have stable market structures, being identified as Emerging is a stronger signal than that sector will encounter larger transformations in the near future. In other words, compared to being Pillar, being Emerging may act as a stronger trigger in transforming market structures.

9 A freely available version of normalized Herfindal-Hirschman Indices for two-digit sectors is available in Bai, Mao, and Zhang (2014). However, their series only go up to 2009, and it is not linkable with other data we may have built upon (e.g., elaborated from Orbis-Bvd database) since the first are normalized taking the 1998 concentration index as equal to 1. Therefore, we could not enter this information into our model.

10 We have also run all the models changing the span of the lag to three years ($Cum\_MA\_y3_{i,t-1}$) and seven years ($Cum\_MA\_y7_{i,t-1}$). The results are consistent with the main results and are available upon request.

for selected sectors, we include a dummy to isolate this potential effect from the main effect we wish to capture. Finally, we also add a dummy variable discriminating before and after 2008. In 2008, in addition to the international economic impact of the global crisis, China somewhat changed its approach towards industrial policy, which has become more systematic and strategic (Jiang & Li, 2010) and increasingly focused on nurturing internal market endogenous growth and resources (Barbieri, Pollio, & Prota, 2020; Di Tommaso et al., 2013). Table 3 reports the summary statistics for the variables of interest and the controls.

All the dependent variables are count nonnegative, with a large concentration on zeros and long right tails. When modeling them, linear models should be excluded in favor of likelihood methods. In this study, we use negative binomial regression with clustered standard errors.[11] Therefore, our baseline model takes the following form:

$$E\left(Y_{i,t}\right) = exp\left(Emerging'_{i,t}\beta_{EM} + \boldsymbol{X}'_{i,t}\boldsymbol{\beta}_{X}\right)$$

where $Y_{i,\,t}$ is the number of M&As (total and by type) for sector *i* at time *t*, *Emerging* is the dummy variable identifying whether sector *i* at time *t* is emerging according to the FYP in force, and $\boldsymbol{X}$ is the vector of controls.

4.2. Endogeneity treatment via three-step IV

To assess causality, we need to limit the possible sources of endogeneity that may arise from potential omitted variables affecting both the variable of interest and the M&A events. To tackle endogeneity, we resort to instrumental variable methods. Since the endogenous variable *Emerging* is a dummy and the outcome of interest (*Number of M&As*) is a count variable, standard 2SLS procedures in our case would generate inconsistent results given the form of the phenomenon and the types of variables we are analyzing.[12] Henceforth, we use a three-step instrumental variable procedure (Adams et al., 2009; Wooldridge, 2010), which is formalized as follows:

1) As a first step, we estimate a binary response model (probit) of the endogenous regressor Emerging (*w* in the following notation) as a function of the instrumental variable (*z*) and the controls ($\boldsymbol{x}$).

$$\mathrm{P}(\mathrm{w} = 1, \mathbf{x}, \mathrm{z}) = G(\boldsymbol{x}, z; \gamma),$$

We obtain the fitted probabilities $\widehat{G}$.

2) We regress *w* on $\widehat{G}$ and **x,** again via probit. We obtain new fitted probabilities $\widehat{G'}$.
3) We regress the outcome of interest $\boldsymbol{Y}$ on $\widehat{G'}$ and **x** via a nonlinear model (negative binomial):

$$E\left(Y_{i,t}\right) = exp\left(\widehat{G'}'_{i,t}\beta_{\widehat{G'}} + \boldsymbol{X}'_{i,t}\boldsymbol{\beta}_{X}\right)$$

Due to this procedure, we are able to take into account the binary nature of the endogenous regressor and to keep the asymptotical validity of the IV standard errors. In addition, although the model for the first stage is not correctly specified, we still obtain consistent estimations (see Wooldridge, 2010 for further details).

In the search for a valid instrument for sectoral identification as emerging, we have referred to the main motivation that, according to various sources in the literature (Chen, 2015; Prud'homme, 2016; Yang, 2015), leads policymakers to identify, since the beginning, the category of emerging sectors within the FYP. As we have highlighted before, emerging sectors are identified as those with the largest innovation and technology growth potential, and those at the international technological frontier, and their development is a core part of China's technological catch-up *vis à vis* the international environment (Prud'homme, 2016). In other words, it can be suggested that the identification of emerging sectors follows technological trends at the global level to some extent. We have exploited this aspect and have constructed an instrument proxying the technology embedded in each sector at the international level. To construct the instrument, we used the OECD database[13] and calculated, for each available sector, country and year, the ratio of R&D

[11] We have instead excluded zero-inflated models since the data-generating process that requires the use of those models (two different populations, one for which the dependent variable can only take the value of zero and the other for which the dependent variable can both take a value zero and different from zero) does not fit the phenomenon we are studying (see, e.g., Greene, 2012). Indeed, negative binomial models are considered to consistently handle variables with large concentration of zeros (Allison, 2012).

[12] Our outcome of interest is a count variable, while the variable of which we wish to study the impact is a dummy variable. Both variables should be modeled via nonlinear techniques (negative binomial for the first and probit/logit for the second). In a two-step procedure, we would need to combine different estimation methods in the first and in the second step. This would lead to inconsistent estimates of the structural parameters (Wooldridge, 2010).

[13] Data are retrieved from OECD Structural analysis and Structural Business databases.

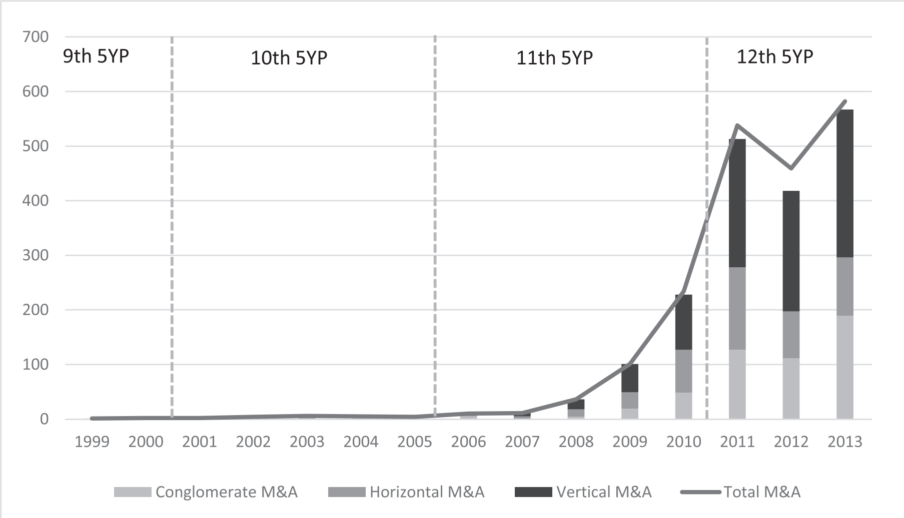

Fig. 1. The trend of M&As, total and by type – year 1999–2013.
Source: authors' elaboration on Zero2IPO data.

employees to total employees. Computing the instrument variable on OECD countries, hence excluding China, ensures that the instrument is not directly related with the outcome of interest of our model (the number of M&A by Chinese firms). We then took the average of the values across countries and across the FYP. We have finally used for each identification as Emerging the data related to the previous FYP, since it is reasonable to assume that the choice of what sectors are promising in terms of technology development is based upon the state of the art during the formation of the FYP and before the official publication. Therefore, for each sector *i*, the final instrument is the average of the ratio of R&D employees to total employees in OECD countries across the five years preceding the issuance of each plan. We expect that the instrument proxying the technological level of the sector will be positively related to the dummy Emerging.

We name the instrumental variable *RD_OECD* and report summary statistics in Table 3.

5. Results

5.1. A description of Chinese M&A

The majority of the 1995 M&As in our database are vertical: 919, corresponding to 46.1%. Conglomerate M&A are 508 (25.5% of the sample), and Horizontal are 481 (24.4%).[14] The entire M&A phenomenon has remained substantially stagnant up to the mid-2000s (corresponding to the 9th and 10th FYPs), with only 3.4 M&A on average each year. During the 11th Five-Year plan period (2006–2010), the number of M&As, in particular vertical and horizontal, started to rise, ranging from 10 in 2006 to 234 in 2010. However, it was only after 2010 that the phenomenon exploded, with the total number ranging between 450 and 600 each year and an acceleration in the number of vertical and conglomerate M&As (Fig. 1).

While all the two-digit sectors in our sample were involved in at least one M&A event between 1999 and 2013, the phenomenon appeared to be rather concentrated (Table 4). In fact, the first 10 sectors for M&As amount to 78% of the total events. This percentage increases to 81.8% for vertical M&As and 81.9% for horizontal M&As, while conglomerate M&As are less clustered, as the first 10 sectors total 72.8% of the events. The sectors with the largest number of M&As can be mainly grouped into three areas: chemicals and pharmaceuticals (approximately 24% of total M&As), instrument and machinery manufacturing (19.8%) and ICT (11.6%). In particular, while pharmaceuticals and chemistry always range among the first three categories in terms of M&As by type, ICT by itself represents 17.5% of vertical M&As.

These M&As are mainly participated by the private sector, that activated 1055 operations, while 470 are realized by national or local SOEs.[15] Following the general trend, both types of M&As remained stagnant and comparable in absolute terms up to the end of the 2000s. After 2010, the trend of events from private firms detaches from that of public acquirers and grows at a larger pace (Fig. 2).

While both private and public acquirers have mainly concentrated on vertical operations, which represent approximately 52% of M&As for both categories, SOEs have been much more involved in relative terms in horizontal M&As than their private peers (Table 5). Indeed, 28.7% of events involving a public acquirer are horizontal M&As, while 16.2% are conglomerate M&As. Conversely, private actors' operations seem to distribute evenly between horizontal (21.7%) and conglomerate (22.3%). In other words, while both private

[14] The remaining 87 events, that is 4.3% of the sample, are not classifiable.
[15] In this case, the number of events for which the information is missing rises to 23.6% of the total sample (470 observations).

Table 4
First 10 target sectors by M&A (total and by type).

Sectors	Events	as % of the total
Total M&A		
Chemical materials and products (26)	243	12.18
Medical and Pharmaceutical Products (27)	238	11.93
ICT (39)	231	11.58
Energy production and Supply (44)	175	8.77
Instrument Manufacturing (40)	174	8.72
Electrical machinery and equipment (38)	143	7.17
Nonmetal mineral products (30)	111	5.56
Nonferrous Metal mining and dressing (9)	92	4.61
Special Equipment Manufacturing (35)	78	3.91
Automotive (36)	73	3.66
Vertical M&A		
ICT (39)	161	17.52
Medical and Pharmaceutical Products (27)	147	16.00
Chemical materials and products (26)	103	11.21
Instrument Manufacturing (40)	91	9.90
Electrical machinery and equipment (38)	73	7.94
Nonmetal mineral products (30)	53	5.77
Special Equipment Manufacturing (35)	40	4.35
Energy production and Supply (44)	34	3.70
Wood products (20)	25	2.72
Ferrous metal processing (31)	25	2.72
Conglomerate M&A		
Energy production and Supply (44)	79	15.55
Chemical materials and products (26)	67	13.19
Instrument Manufacturing (40)	35	6.89
ICT (39)	34	6.69
Nonferrous Metal mining and dressing (9)	32	6.30
Electrical machinery and equipment (38)	31	6.10
Medical and Pharmaceutical Products (27)	28	5.51
Nonmetal mineral products (30)	28	5.51
Wood products (20)	21	4.13
Ferrous metal processing (31)	15	2.95
Horizontal M&A		
Chemical materials and products (26)	68	14.14
Medical and Pharmaceutical Products (27)	57	11.85
Energy production and Supply (44)	52	10.81
Automotive (36)	38	7.90
ICT (39)	35	7.28
Nonferrous Metal mining and dressing (9)	33	6.86
Electrical machinery and equipment (38)	32	6.65
Beverage industry (15)	29	6.03
Nonmetal mineral products (30)	27	5.61
Instrument Manufacturing (40)	23	4.78

Source: authors' elaboration on Zero2IPO data.

and public firms have been greatly involved in integrating activities via vertical M&As, SOEs have spent relatively more energy rationalizing the market where they were operating rather than seeking opportunities in other sectors.

5.2. *Econometric analysis: Results and discussion*

5.2.1. *Baseline results*

Table 6 reports the baseline results of the negative binomial regressions. The first evidence on total M&As (column 1) highlights that identification as *emerging* in the FYP is positively associated with a larger number of M&A events. Pillar sectors also seem to show a positive association with M&As, although the significance is less prominent than for emerging sectors.

The results for the different types of M&As (columns 2–4) mostly confirm the general result for emerging sectors, if we exclude conglomerate M&As (column 3). Both horizontal and vertical M&A events appear to be more frequent in emerging sectors, while we do not find any significant correlation between *Emerging* dummy and conglomerate M&A.

Regarding pillar sectors, on the other hand, we do not observe any relevant potential effects on M&As, which may be a sign that these sectors have already reached maturity – and connected to the fact that a lesser number of supporting measures are in place. Therefore, pillar sectors may no longer be able to attract new resources from other sectors, or there is no longer an incentive for firms to increase in their average size.

The signs and significance of the other controls on the various M&A types also provide useful insights into the phenomenon under

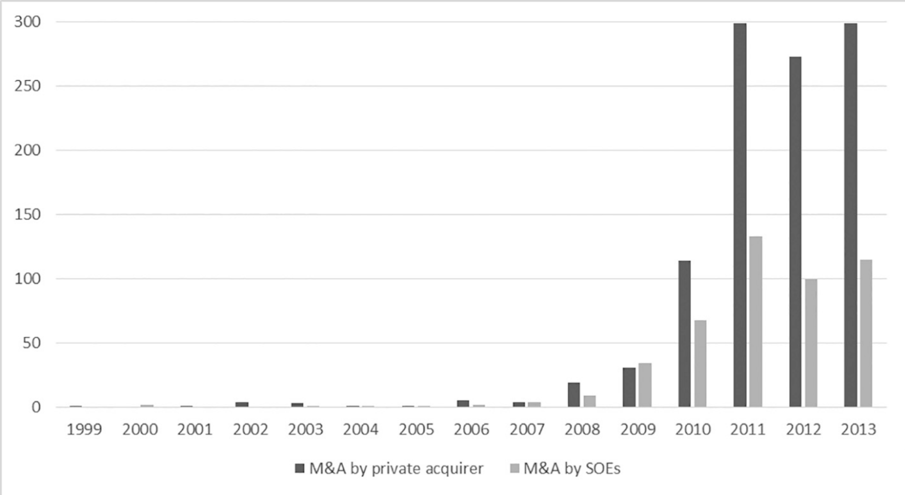

Fig. 2. Trend of M&As by nature of the acquirer (private versus SOEs).
Source: authors' elaboration on Zero2IPO data.

Table 5
Distribution by type of M&A of SOEs and private firms' operations.

Acquirer	Horizontal M&A		Vertical		Conglomerate		*Undefined*	
	Events	(As %)	Events	(As %)	Events	(As %)	*Events*	*(As %)*
SOE	135	(28.7)	244	(51.9)	76	(16.2)	*15*	*(3.2)*
Private	229	(21.7)	545	(51.9)	235	(22.3)	*46*	*(4.3)*

Source: authors' elaboration on Zero2IPO data.

scrutiny. First, all types of M&A events appear to be more frequent during the 11th and 12th FYPs compared to the base category (the 10th FYP). Since we include in the model the post-2008 dummy catching the postcrisis economic cycle, these effects may be attributed to the plans themselves. Indeed, these are the FYPs that point towards industrial rationalization and efficiency increases the most. In doing so, they also explicitly cite the necessity to go towards increases in average size and reductions in market fragmentations with M&As.

For the variables referring to the sectors' economic features, we do not observe any relation between M&As and those variables that serve as a proxy for the sector's profitability ($ROA_{i,t}$), the financial structure ($DEBT\_RATIO_{i,t}$) and the presence of SOEs in the sector ($SOE\_RATE_{i,t}$). The size of the sector ($FIRMS_{i,t}$) seems to positively influence the amount of vertical and conglomerate M&As. More interestingly, $FIRMS\_SIZE_{i,t}$ is positively correlated with vertical and total M&As. This may suggest that vertical M&As (which, given their number, influence the results on total M&As) are more plausible when the sector has on average already reached a certain degree of scale efficiency, while the latter may be the general objective of horizontal M&As. $LOSS\_FIRMS\_RATIO_{i,t}$ is negatively associated with total M&A events. In terms of past dynamics reflected in previous years' M&As, the general evidence is that previous M&As, both on a yearly basis and cumulated across a five-year period, are positively associated with current M&A events, or at most, they do not affect the latter. This would suggest that economic actors do not react negatively to previous M&A waves and that these can act as a symptom of sectoral dynamism and attract firms to continue M&A operations.

Finally, contrary to previous empirical evidence (Chen et al., 2020), we do not find that OCMA policy has had any additional effect on M&As once the indications by FYPs are introduced in the model.

5.2.2. *Endogeneity treatment: Three-step IV*

In this section, we present the results when we apply the three-step IV using the average technology intensity by sector in OECD countries in the five-year span before each FYP (*RD_OECD*) as an instrument of the Emerging dummy. In Table 7, we report the first-step binary response – probit model (column 1) and the third-step total M&A (column 2).

As we expected, the instrumental variable *RD_OECD* is positively and strongly correlated with *Emerging*. This, coupled with the F-statistic obtained from a linear version of the first step, indicates that our instrument is strong. Moving to the third step in which we use the instrumented *emerging* variable (column 2), we find a confirmation that the associated coefficient is positive and significant. In this case, unlike the baseline version, we can interpret this as a causal relation, that being identified as emerging exerts a positive effect on the number of M&As in a sector. In other words, emerging sectors tend to have a more dynamic market structure than others. The results for all the controls are stable with respect to the baseline results (Table 6, column 1), except for the pillar identification, which becomes nonsignificant.

Table 6
Baseline results.

	(1)	(2)	(3)	(4)
	$M\&A\_TOT_{i,t}$	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{i,t}$	$M\&A\_CONGL_{i,t}$
$Emerging_{i,t}$	0.864**	0.953**	0.772**	0.326
	(2.43)	(2.52)	(2.04)	(0.93)
Pillar $(only)_{i,t}$	0.663*	0.59	0.702	0.063
	(1.81)	(1.50)	(1.51)	(0.19)
11th FYP	1.153***	0.842*	1.217**	1.168**
	(3.70)	(1.94)	(2.39)	(2.02)
12th FYP	1.514***	1.262***	1.144**	2.018***
	(4.53)	(2.63)	(2.27)	(3.87)
$ROA_{i,t}$	0.001	0.006	0.001	−0.004
	(0.22)	(1.09)	(0.11)	(−0.64)
$FIRMS_{i,t}$	0.029	0.033*	0.006	0.048***
	(1.46)	(1.70)	(0.34)	(2.78)
$LOSS\_FIRMS\_RATIO_{i,t}$	−0.011**	−0.007	−0.01	0.002
	(−2.01)	(−1.51)	(−1.54)	(0.30)
$FIRMS\_SIZE_{i,t}$	0.002***	0.003***	0.001	−0.006
	(2.61)	(5.09)	(0.39)	(−1.20)
DEBT_RATIOi,t	−0.025	−0.02	−0.027	−0.013
	(−0.71)	(−0.62)	(−0.83)	(−0.42)
SOE_RATEi,t	−0.008	−0.015	−0.005	0
	(−0.42)	(−0.83)	(−0.33)	(0.03)
$PROD\_GROWTH_{i,t}$	−0.097	0.367	0.813*	−0.327
	(−0.23)	(0.80)	(1.90)	(−0.85)
$M\&A\_TOT_{i,t-1}$	0.067***			
	(3.36)			
$M\&A\_VER_{i,t-1}$		0.039		
		(1.58)		
$M\&A\_HOR_{i,t-1}$			0.190***	
			(3.50)	
$M\&A\_CONGL_{i,t-1}$				0.083***
				(2.71)
$Cum\_MA\_y5_{i,t}$	−0.004	0.016*	0.012***	0.010**
	(−0.47)	(1.95)	(3.36)	(2.19)
OCMA	−0.269	−0.345	−0.623	−0.279
	(−0.72)	(−1.07)	(−1.14)	(−1.00)
Constant	−1.044	−2.173	−2.031	−3.186*
	(−0.54)	(−1.14)	(−1.09)	(−1.89)
Post 2008 dummy	Y	Y	Y	Y
N	396	396	396	396
Likelihood ratio test of alpha = 0[a]	883.45***	361.73***	234.87***	114.13***
log-likelihood	−638.564	−453.461	−376.538	−355.638
BIC	1378.813	1008.605	854.76	904.393
AIC	1311.129	940.921	787.076	841.142
chi2	822.215***	686.828***	333.886***	1907.707***
Pseudo_R2	0.207	0.237	0.224	0.263

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1. All models are negative binomial with clustered standard errors.

[a] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table 8 reports the IV results by the three types of M&As. Once endogeneity is taken into account, the effect of *Emerging* on M&As appears to be positive for all M&A types, including conglomerate types. Regarding vertical M&As (column 1), firms in emerging sectors act to increase vertical integration. This is consistent with the fact that emerging sectors tend to be those with more technological advance prospects: in these sectors, firms may need to increase the process and product quality more than in other sectors and to prepare to do so, they may increase vertical integration to gain control of the overall quality of production (Miliou, 2004; Schweiger & Very, 2003; Barbieri et al., 2017).

The positive sign associated with horizontal M&As (column 2), on the other hand, suggests that firms in emerging sectors appear to rationalize and look for efficiency advantages through increases in average size. This trend would highlight an alignment between public policy objectives and firms' behavior, in which increased market concentration is not seen as a threat but as a desirable economy-wide goal. This process would be in line with the literature emphasizing that industrial policies towards infant industries encourage the emergence of national champions able to compete in international markets (Chang, 2008; Nolan, 2001).

Finally, with respect to conglomerate M&A (column 3), actors may move towards emerging sectors to gain advantages in terms of subsidies that will be devoted to those sectors. On the one hand, this could be regarded as an opportunistic rent-seeking behavior by firms aiming at reaping the benefits of increased subsidies or easier access to credit, in line with the traditional government failure literature (Tullock, 2013; Wedeman, 2003). Given the disadvantages and possible inefficiencies related to new entrants' insufficient

Table 7
Three-step IV results – $M\&A\_TOT_{i,t}$.

	$M\&A\_TOT_{i,t}$	
	(1)	(2)
$RD\_OECD_{i,t}$	27.831***	
	(4.44)	
$Emerging_{i,t,}$		1.207***
		(3.12)
Pillar (only)$_{i,t}$ [a]		0.265
		(0.94)
11th FYP	6.251***	0.831**
	(3.50)	(2.36)
12th FYP	7.042***	1.207***
	(3.61)	(3.44)
$ROA_{i,t}$	−0.021*	0.007
	(−1.74)	(1.33)
$FIRMS_{i,t}$	0.084**	0.03
	(2.07)	(1.58)
$LOSS\_FIRMS\_RATIO_{i,t}$	0.245*	−0.011**
	(1.93)	(−2.25)
$FIRMS\_SIZE_{i,t}$	−0.280*	0.002**
	(−1.96)	(2.56)
DEBT_RATIOi,t	0.026	−0.003
	(1.03)	(−0.11)
SOE_RATEi,t	0.018**	−0.001
	(2.00)	(−0.05)
$PROD\_GROWTH_{i,t}$	−0.722**	−0.138
	(−2.45)	(−0.33)
$M\&A\_TOT_{i,t-1}$	−0.005	0.057***
	(−0.22)	(2.73)
$Cum\_MA\_y5_{i,t}$	−0.005	−0.002
	(−0.46)	(−0.23)
OCMA	−0.775	−0.17
	(−1.25)	(−0.49)
Constant	−9.561***	−2.279
	(−4.43)	(−1.26)
Post 2008 dummy	Y	Y
N	360	360
First stage F-stat (linear)[b]	36.00***	
Likelihood ratio test of alpha = 0[c]		857.77**
log-likelihood	−76.275	−581.523
BIC	240.841	1263.11
AIC	182.55	1197.047
chi2	822.215***	715.249***
Pseudo_R2	0.555	0.208

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The first stage F-statistic is obtained from the OLS version with robust standard errors.

[c] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

means and knowledge of the sector that the literature highlights (Scharfstein and Stein, 2000; Berger & Ofek, 1995; Lang & Stulz, 1994; Jensen, 1986), these investments may risk endangering the performance of emerging sectors.

On the other hand, however, this increase is consistent with the entire incentive and signaling system of the policy, which aims at leading more economic means towards these new strategic activities. In this sense, the results on conglomerate M&As may be read exactly as the result of the policy effort to overcome a coordination failure – where no individual actor has the incentive to be a first mover (Andreoni & Chang, 2019) – and to change structural interdependencies among actors (Cardinale et al., 2017; Cardinale & Scazzieri, 2019).

To better qualify the results, we separately analyze the M&As realized by private firms and SOEs (Table 9). First, both private and public firms appear to actively engage in M&As in emerging industries (columns a.1 and b.1). This may suggest that the policy indication is able to orient not only SOEs but also private actors in contributing to the structural change of the market for those sectors.

Table 8
Three-step IV results – by type of M&A.[c]

	(1)	(2)	(3)
	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{i,t}$	$M\&A\_CONGL_{i,t}$
$Emerging_{i,t,}$	1.467***	1.004**	0.674**
	(3.97)	(2.37)	(2.02)
Pillar $(only)_{i,t}$[a]	0.262	0.3	−0.071
	(0.90)	(0.86)	(−0.29)
11th FYP	0.579	0.909	0.987
	(1.30)	(1.62)	(1.60)
12th FYP	1.113**	0.839	1.679**
	(2.38)	(1.52)	(2.43)
$ROA_{i,t}$	0.010*	0.008	0.001
	(1.72)	(1.53)	(0.15)
$FIRMS_{i,t}$	0.035**	0.007	0.043**
	(1.97)	(0.33)	(2.50)
$LOSS\_FIRMS\_RATIO_{i,t}$	−0.007*	−0.010*	0.002
	(−1.77)	(−1.70)	(0.31)
$FIRMS\_SIZE_{i,t}$	0.003***	0.001	−0.006
	(5.29)	(0.35)	(−1.16)
DEBT_RATIOi,t	−0.006	−0.001	−0.001
	(−0.21)	(−0.04)	(−0.04)
SOE_RATEi,t	−0.009	0.004	0.004
	(−0.51)	(0.27)	(0.25)
$PROD\_GROWTH_{i,t}$	0.448	0.597*	−0.586*
	(0.94)	(1.73)	(−1.83)
$M\&A\_VER_{i,t-1}$	0.035		
	(1.60)		
$M\&A\_HOR_{i,t-1}$		0.163***	
		(2.81)	
$M\&A\_CONGL_{i,t-1}$			0.096***
			(2.64)
$Cum\_MA\_y5_{i,t}$	0.015*	0.009***	0.007*
	(1.89)	(2.59)	(1.85)
OCMA	−0.18	−0.453	−0.141
	(−0.69)	(−0.87)	(−0.55)
Constant	−2.949	−3.499**	−3.852**
	(−1.60)	(−2.01)	(−2.43)
Post 2008 dummy	Y	Y	Y
N	360	360	360
Likelihood ratio test of alpha = 0[b]	467.79***	196.13***	93.33***
log-likelihood	−415.459	−341.527	−322.549
BIC	930.981	783.117	745.162
AIC	864.917	717.053	679.099
chi2	611.963***	361.577***	615.754***
Pseudo_R2	0.241	0.23	0.269

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.
[a] The dummy "Pillar" is omitted in the first step due to collinearity.
[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.
[c] For the sake of readability, the table only reports the third steps of the IV procedures. The first steps are reported in the appendix, Table A1.

However, private firms and SOEs seem to behave differently according to the different types of M&As we take into account. Both private firms and SOEs increase vertical M&As in emerging sectors compared to nonmentioned sectors (columns a.2 and b.2).[16] This result reflects the main one and seems to attribute to both types of firms strategic behaviors to increase their control over the production chain in the expectation that they will need larger efforts to increase technology and quality embodied in the products.

However, only private firms are responsive in terms of horizontal M&As in emerging sectors (column a.3), while there appears to be no relation between being in an emerging sector and the number of horizontal M&A SOEs carry out (b.3). While private firms in emerging sectors may work not only to increase sectoral rationalization but also to increase size and potentially scale efficiency, this is not the case for SOEs. This is somewhat expected: rationalization via M&As is more likely to happen when the productive environment has a certain degree of fragmentation (Barbieri et al., 2017). In the case of SOEs, the consolidation of the public sector, with a substantial decrease in the number of firms and the increase in size of the remaining firms, was already carried out in China massively and

[16] The table only reports the variables of interest for the third IV step. The full regressions are reported in the Appendix (Tables A2 and A3), while the coefficients and the version with cumulative M&A in the previous three and seven years, together with the regressions of the first steps, are available upon request.

Table 9
Three-step IV results – by type of acquiror.

a. M&A by private firms

	(a.1)	(a.2)	(a.3)	(a.4)
	MA_TOT_priv	MA_VER_priv	MA_HOR_priv	MA_CONGL_priv
Emergingi,t	1.292***	1.673***	1.056**	0.232
	(3.33)	(4.41)	(2.17)	(0.61)
N	360	360	360	360
Likelihood ratio test of alpha = 0	857.77***	216.10***	61.08***	16.98***
Log-likelihood	−432.205	−307.603	−234.141	−199.59
BIC	964.473	715.269	568.346	499.244
AIC	898.409	649.206	502.283	433.18
chi2	914.657***	629.841***	707.291***	2077.824***
Pseudo_R2	0.257	0.29	0.251	0.341

b. M&A by SOEs

	(b.1)	(b.2)	(b.3)	(b.4)
	MA_TOT_pub	MA_VER_pub	MA_HOR_pub	MA_CONGL_pub
Emergingi,t	0.955**	1.078**	0.938	0.503
	(2.29)	(2.09)	(1.46)	(0.90)
N	360	360	360	360
Likelihood ratio test of alpha = 0[a]	154.00***	70.77***	37.40***	13.22***
Log-likelihood	−329.02	−236.838	−171.965	−125.337
BIC	758.104	573.74	443.993	350.737
AIC	692.04	507.676	377.929	284.673
chi2	193.665***	143.005***	344.020***	174.436***
Pseudo_R2	0.256	0.269	0.234	0.284

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.

[a] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

horizontally across the sectors between the end of the 1990s and the first years of the 2000s (Hsieh & Zheng, 2015).

5.2.3. Robustness checks

To conclude the empirical investigation, we run some robustness checks. First, Fig. 1 shows that the majority of the M&A events are concentrated in the 11th and 12th FYPs, while in the 10th FYP, the number seems negligible. This trend is horizontal across types of M&As, regardless of whether they are carried out by the public or the private sector. This may cast some doubts on whether the M&A trends, rather than being generated by the FYP and the identification of emerging sectors, are related to global uncertainty. To reinforce our analysis, therefore, we have rerun the model focusing only on the last two FYPs under analysis, reported in Table 10.

Since the likelihood test on alpha = 0 for conglomerate M&As (Table 10, column 4) does not exclude that the generating process is Poisson, we also report the Poisson version (Table 10, column 5). The results generally confirm the positive and significant effects of being identified as an emerging sector on all types of M&As, with the exception of conglomerate M&As in the Poisson version. This suggests that, with this latter exception, even when controlling for the international uncertainty triggered by the global crisis, sectoral identification still plays a role in influencing M&A events.

Second, as we have previously pointed out (section 2.2), existing literature stresses the relevant role of the political dimension in affecting the economic performance. While we have already taken into account the direct influence on firm-level M&As, by analyzing SOEs and private firms separately, a role of politics might also be relevant in affecting macroeconomic fluctuations and capital formation. In particular, recent contributions have highlighted the role and peculiarity of Chinese Political Business Cycle (Li, 2011; Yanbing, 2015). These studies have observed macroeconomic fluctuations soon before or after relevant meeting of national political bodies. This is explained by the system of promotion and penalty for local policymakers, causing them to make an effort to obtain and show positive economic performances in proximity of such meeting, so to favor a career boost. In the context of our paper, local policymakers wishing to increase gross capital formation might favor a rise in the average firm size through M&As. To exclude that this aspect biases the results on selected emerging sectors, we have added three dummy variables controlling for 1) the years when National Congress of the Communist Party of China (CPC) meetings take place (*CPC_YEAR*), 2) the years immediately before the CPC meeting (*CPC_BEFORE*), and 3) the years immediately after the CPC meetings (*CPC_AFTER*).[17] The results are reported in Table 11. In this case, since the likelihood test on $\alpha = 0$ does not exclude that the generating process is Poisson for any of the M&A types, we only report

[17] We have also run a series of regressions in which we add the three dummies separately. The results are consistent with the main ones and are available upon request.

Table 10
Three-step IV results on last two FYPs – by type of M&A.

	(1)	(2)	(3)	(4)	(5)
	$M\&A\_TOT_{i,t}$	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{i,t}$	$M\&A\_CONGL_{i,t}$ (negative binomial)	$M\&A\_CONGL_{i,t}$ (poisson)
$Emerging_{i,t,}$	1.060***	1.382***	0.795**	0.605**	0.38
	(2.78)	(4.28)	(1.97)	(2.04)	(1.35)
Pillar $(only)_{i,t}$[a]	0.154	0.172	0.185	−0.057	−0.143
	(0.53)	(0.67)	(0.57)	(−0.24)	(−0.72)
12th FYP	0.386**	0.693***	−0.05	0.701***	0.954***
	(2.03)	(4.54)	(−0.16)	(2.84)	(4.69)
$ROA_{i,t}$	0.006	0.007	0.006	0.043**	−0.001
	(0.89)	(1.16)	(0.98)	(2.54)	(−0.09)
$FIRMS_{i,t}$	0.032	0.039**	0.013	−0.122	0.034***
	(1.62)	(2.34)	(0.65)	(−0.94)	(2.92)
$LOSS\_FIRMS\_RATIO_{i,t}$	−0.212	−0.319**	−0.242	0.126	−0.141
	(−1.11)	(−2.47)	(−1.58)	(0.90)	(−1.24)
$FIRMS\_SIZE_{i,t}$	0.213	0.333**	0.245	−0.005	0.151
	(1.04)	(2.39)	(1.48)	(−0.16)	(1.24)
DEBT_RATIOi,t	0.002	−0.01	−0.003	0.002	0.01
	(0.07)	(−0.30)	(−0.08)	(0.11)	(0.43)
SOE_RATEi,t	0	−0.011	0.005	−0.414	0.013
	(−0.03)	(−0.52)	(0.33)	(−1.03)	(0.90)
$PROD\_GROWTH_{i,t}$	0.031	1.104*	0.964**	−0.586*	0.125
	(0.09)	(1.74)	(2.14)	(−1.83)	(0.33)
$M\&A\_TOT_{i,t-1}$	−0.01				
	(−0.49)				
$M\&A\_VER_{i,t-1}$		0.022			
		(1.03)			
$M\&A\_HOR_{i,t-1}$			0.169***		
			(3.00)		
$M\&A\_CONGL_{i,t-1}$				0.110***	0.075***
				(3.10)	(3.03)
$Cum\_MA\_y5_{i,t}$	0.005	0.017**	0.009**	0.006*	0.004
	(0.54)	(2.15)	(2.00)	(1.71)	(0.92)
OCMA	0.042	−0.244	−0.405	−0.169	−0.013
	(0.07)	(−0.94)	(−0.75)	(−0.68)	(−0.06)
Constant	−1.9	−2.355	−2.603	−2.675	−3.587**
	(−1.17)	(−1.23)	(−1.30)	(−1.49)	(−2.25)
Post 2008 dummy	Y	Y	Y	Y	Y
N	240	240	240	240	240
Likelihood ratio test of alpha = 0[b]	42.83***	6.88***	3.08**	0.15	
log-likelihood	−77.833	−381.156	−316.547	−308.524	−352.355
BIC	232.395	850.003	720.785	704.737	786.92
AIC	183.666	794.313	665.095	649.047	734.71
chi2	87.793***	400.881***	267.450***	171.564***	330.920***
Pseudo_R2	0.432	0.2	0.177	0.208	0.552

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%.
[a] The dummy "Pillar" is omitted in the first step due to collinearity.
[b] The likelihood ratio test of alpha = 0 is obtained from the negative binomial regressions without clustered standard errors.

Poisson regressions.[18] Also in this case, our main findings are confirmed, with the exception, once again, of conglomerate M&As.

Finally, the causal interpretation of our results might be biased by potential simultaneity issues related to the controls, given that the variables proxying economic performance and market structure might be affected by the number of M&As in the same year. To mitigate the potential bias arising from this, we have run the regressions for all M&As and for each type of M&A substituting the economic performance and market structure variables with their one-year, three-year or five-year lags. Results are reported in the Appendix (Tables A5 to A8) and are proved consistent with the main ones.

6. Discussion and conclusion

This article empirically investigates the relation between selective policies and M&A waves at the industry level, focusing on the Chinese case and sectoral identification in the FYPs. The empirical analysis we have performed provides some answers to the explorative research questions we have formulated, also in terms of policy implications. First, it seems that the identification of sectors emerging in the FYPs can positively affect M&A events, influencing a restructuring of the markets (ERQ1). This role is played almost horizontally across the types of M&As, although some caution may be used when interpreting the results on conglomerate M&As.

[18] Negative binomial versions and likelihood test on alpha = 0 are reported in the Appendix, Table A4.

Table 11
Three-step IV results controlling for political business cycle.

	(1)	(2)	(3)	(4)
	$M\&A\_TOT_{i,t}$	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{,t}$	$M\&A\_CONGL_{i,t}$
$Emerging_{i,t,}$	0.474*	0.560**	0.886**	0.358
	(1.70)	(2.51)	(1.96)	(1.45)
Pillar (only)$_{i,t}$[a]	0.16	0.187	0.24	−0.104
	(0.83)	(0.99)	(0.73)	(−0.50)
11th FYP	1.290***	1.11	0.941	1.354
	(2.63)	(1.43)	(1.20)	(1.30)
12th FYP	1.909*	1.685	1.304	2.688
	(1.68)	(1.02)	(0.88)	(1.27)
$ROA_{i,t}$	0.005	0.004	0.008	−0.001
	(0.95)	(0.50)	(1.01)	(−0.25)
$FIRMS_{i,t}$	0.008	0.022	0.007	0.033***
	(0.72)	(1.63)	(0.48)	(3.11)
$LOSS\_FIRMS\_RATIO_{i,t}$	−0.002	−0.002	−0.001	0.009
	(−0.61)	(−0.47)	(−0.22)	(0.47)
$FIRMS\_SIZE_{i,t}$	0.004***	0.005***	0.002	−0.006
	(4.49)	(4.02)	(1.32)	(−0.29)
DEBT_RATIOi,t	0.007	0.006	0.01	0.007
	(0.30)	(0.24)	(0.38)	(0.29)
SOE_RATEi,t	0.008	−0.005	0.017	0.013
	(0.59)	(−0.24)	(1.17)	(0.96)
$PROD\_GROWTH_{i,t}$	0.312	0.532	1.114	0.001
	(0.43)	(0.51)	(1.49)	(0.00)
$M\&A\_TOT_{i,t-1}$	0.053***			
	(4.53)			
$M\&A\_VER_{i,t-1}$		0.091***		
		(4.82)		
$M\&A\_HOR_{i,t-1}$			0.065**	
			(2.10)	
$M\&A\_CONGL_{i,t-1}$				0.077***
				(3.18)
$Cum\_MA\_y5_{i,t}$	−0.007	−0.005	0.008**	0.005
	(−1.17)	(−1.14)	(2.08)	(1.25)
CPC_YEAR	−0.908	−0.587	−0.908	−0.804
	(−1.21)	(−0.55)	(−1.00)	(−0.62)
CPC_AFTER	0.087	0.263	0.206	−0.453
	(0.14)	(0.25)	(0.30)	(−0.38)
CPC_BEFORE	0.193	0.35	0.419	−0.192
	(0.27)	(0.38)	(0.47)	(−0.16)
OCMA	0.008	−0.155	−0.29	0.06
	(0.04)	(−0.62)	(−0.69)	(0.30)
Constant	−2.711*	−3.445**	−4.365**	−4.170**
	(−1.83)	(−1.98)	(−2.36)	(−2.52)
Post 2008 dummy	Y	Y	Y	Y
FYP dummies	Y	Y	Y	Y
N	360	360	360	360
BIC	1953.908	1258.685	926.191	833.471
AIC	1880.072	1184.85	852.355	759.635
chi2	4309.622***	1123.795***	2903.735***	4063.167***
Pseudo_R2	0.72	0.679	0.562	0.629

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are Poisson with clustered standard errors.
[a] The dummy "Pillar" is omitted in the first step due to collinearity.

These, in turn, may have been more triggered by international uncertainty or political business cycles factors than by policy indications (ERQ2). Finally, in terms of the types of firms that realize M&As, identification as emerging sectors is able to push both private firms and SOEs to increase vertical integration in the plausible search for larger gained control above the entire production chain to improve its quality and performance. In addition, the FYP identifying emerging sectors can also encourage industrial rationalization in the private sector via horizontal M&As, while this seems not to be the case for SOEs that have been subject to homogeneous rationalization processes in the first years of the twenty-first century (ERQ3). Finally, although the results are not as robust as the others, some warnings should be raised with respect to the positive effects of emerging identification on conglomerate M&As. In this case, indeed, firms may aim at exploiting either direct advantages coming from policy subsidies devoted to the sector or indirect ones linked to the expected growth of the emerging sector. While this behavior may be consistent with the general policy of pushing growth in these sectors, it must be underlined that this can trigger rent seeking and firm dependency upon public subsidies, which can hamper the efficient development of these sectors.

Overall, the findings of our study seem to suggest that Chinese FYPs may effectively be able to affect economic actors' behavior by reorienting firm strategies within and across sectors. Our evidence on the Chinese case can be useful for the wider study of the relation between policies and structural changes in industries. In particular, our paper suggests that industrial policy measures, as well as the expectations generated by their announcements, can be significant tools to generate – intended or unintended - changes in markets and sectors and that further studies are needed to explore these relations in other countries and economic regions with different varieties of capitalism.

Our paper also contributes to the literature on M&As, suggesting that they may not just be related to strategic individual behaviors activated by firms, but also stimulated by governments as a tool to promote structural changes in the sectors' market and, overall, in the economy. In this view, a new role for strategic industrial policy is highlighted as a means to shape new market structures. Previous literature on industrial policies in relation to M&As mainly underlined the anti-trust role of governments to strengthen competition (Anderson et al., 2013; Chen et al., 2020; James & Wier, 1987). Other studies, however, have highlighted that governments may also consider certain degrees of market concentration as desirable, and therefore choose to encourage them. For example, restructuring of specific sectors has been favored for strategic reasons (Di Tommaso & Tassinari, 2017; Tassinari, 2019), or to nurture infant industries consistently with the national developmental plans (Chang, 2002, 2008). Our contribution shows that the Chinese government has the possibility to induce changes in the degree of market concentration, even only by stressing the relevance of certain sectors in its planning strategies. However, if the objective of emerging identification is to foster a transformation in the sector in terms of increases in performance and technological endowments, it remains to be seen whether policy-induced M&As successfully bring about these improvements. In order for this to happen, policy choices should be based on evidence evaluating the impact of M&A waves on economic and innovation performances. This goes beyond the scope of our paper, yet it is a central aspect. Future studies could indeed go more in depth on the potential effects on technological and economic performance of these sectors in which policy incentives have generated a restructuring of the markets.

Finally, our paper suggests that new attention should be given not only to the content of industrial policies but also to the way industrial-policy initiatives are communicated to markets, since this aspect, similar to other spheres of policy initiatives, can also trigger larger effects and actions by individual actors. It is thus crucial for governments to acquire a certain ability to correctly communicate policy choices to the external environment, and the incapability to efficaciously and consistently do so may lead to government failures in generating the expected results from the policy measures.

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Appendix A

Table A1
Three-step IV– first step by type of M&A.

	(1)	(2)	(3)
	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{i,t}$	$M\&A\_CONGL_{i,t}$
$RD\_OECD_{i,t}$	28.336***	27.576***	27.940***
	(4.18)	(4.61)	(4.53)
11th FYP	6.394***	6.199***	6.310***
	(3.36)	(3.64)	(3.67)
12th FYP	7.191***	6.947***	7.059***
	(3.50)	(3.72)	(3.73)
$ROA_{i,t}$	−0.021*	−0.021*	−0.021*
	(−1.76)	(−1.78)	(−1.78)
$FIRMS_{i,t}$	0.085**	0.084**	0.084**
	(2.06)	(2.02)	(2.03)
$LOSS\_FIRMS\_RATIO_{i,t}$	0.235**	0.210**	0.204*
	(2.02)	(1.98)	(1.83)
$FIRMS\_SIZE_{i,t}$	−0.268**	−0.245*	−0.237*
	(−2.09)	(−1.94)	(−1.83)
DEBT_RATIOi,t	0.024	0.025	0.023
	(0.90)	(0.98)	(0.96)
SOE_RATEi,t	0.018**	0.017*	0.016*
	(1.86)	(1.83)	(1.86)

(continued on next page)

Table A1 (*continued*)

	(1)	(2)	(3)
	M&A_VER$_{i,t}$	M&A_HOR$_{i,t}$	M&A_CONGL$_{i,t}$
PROD_GROWTH$_{i,t}$	−0.636**	−0.797**	−0.780**
	(−2.23)	(−2.42)	(−2.55)
M&A_VER$_{i,t-1}$	−0.024		
	(−0.40)		
M&A_HOR$_{i,t-1}$		0.028	
		(0.44)	
M&A_CONGL$_{i,t-1}$			0.042
			(0.60)
Cum_MA_y5$_{i,t}$	−0.002	−0.009	−0.012
	(−0.11)	(−1.15)	(−1.16)
OCMA	−0.754	−0.762	−0.708
	(−1.21)	(−1.22)	(−1.14)
Constant	−9.595***	−9.379***	−9.407***
	(−4.39)	(−4.45)	(−4.38)
Post 2008 dummy	Y	Y	Y
N	360	360	360
First stage F-stat (linear)[a]	36.47***	36.73***	37.46***
log-likelihood	−76.142	−76.192	−76.078
BIC	240.576	240.675	240.447
AIC	182.285	182.383	182.155
chi2	82.239***	99.757***	77.861***
Pseudo_R2	0.556	0.556	0.556

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors. The dummy "Pillar" is omitted in the first step due to collinearity.

[a] The first stage F-statistic is obtained from the OLS version with robust standard errors.

Table A2

Three-step IV results – M&A by private firms (total and by type).

	(1)	(2)	(3)	(4)
	MA_TOT_priv	MA_VER_priv	MA_HOR_priv	MA_CONGL_priv
Emerging$_{i,t}$	1.292***	1.673***	1.056**	0.232
	(3.33)	(4.41)	(2.17)	(0.61)
Pillar (only)$_{i,t}$	0.475	0.479*	0.654*	−0.231
	(1.60)	(1.65)	(1.79)	(−1.16)
11th FYP	1.067*	0.696	1.056	154.590*
	(1.83)	(1.21)	(1.29)	(1.66)
12th FYP	1.692***	1.404**	1.161	155.892*
	(2.74)	(2.29)	(1.36)	(1.67)
ROA$_{i,t}$	0.011**	0.011*	0.012*	0.005
	(2.03)	(1.65)	(1.82)	(0.76)
FIRMS$_{i,t}$	0.015	0.016	0	0.046***
	(0.79)	(0.87)	(−0.00)	(2.89)
LOSS_FIRMS_RATIO$_{i,t}$	−0.011**	−0.008**	−0.011*	−0.208
	(−2.30)	(−2.02)	(−1.66)	(−1.59)
FIRMS_SIZE$_{i,t}$	0.004***	0.005***	0.002	0.218
	(4.19)	(5.23)	(1.13)	(1.55)
DEBT_RATIOi,t	0.002	−0.014	−0.001	0.031
	(0.08)	(−0.46)	(−0.04)	(1.24)
SOE_RATEi,t	0.003	−0.015	0.004	0.023*
	(0.23)	(−0.85)	(0.20)	(1.76)
PROD_GROWTH$_{i,t}$	0.561	0.377	0.733*	0.624
	(1.19)	(0.67)	(1.74)	(1.15)
M&A_TOT_priv$_{i,t-1}$	0.02			
	(0.80)			
M&A_VER_priv$_{i,t-1}$		0.051*		
		(1.65)		
M&A_HOR_priv$_{i,t-1}$			0.217**	
			(2.47)	
M&A_CONGL_priv$_{i,t-1}$				0.105***
				(2.60)
Cum_MA_y5$_{i,t}$	0.020**	0.016*	0.007	0.008**
	(2.36)	(1.81)	(1.47)	(2.30)
OCMA	−0.338	−0.09	−0.501	−0.508**
	(−0.93)	(−0.28)	(−0.82)	(−2.52)
Constant	−3.810**	−3.180*	−4.536**	−160.538*
	(−2.27)	(−1.67)	(−2.51)	(−1.72)

(*continued on next page*)

Table A2 (*continued*)

	(1) MA_TOT_priv	(2) MA_VER_priv	(3) MA_HOR_priv	(4) MA_CONGL_priv
Post 2008 dummy	Y	Y	Y	Y
N	360	360	360	360
Likelihood ratio test of alpha = 0[a]	857.77***	216.10***	61.08***	16.98***
log-likelihood	−432.205	−307.603	−234.141	−199.59
BIC	964.473	715.269	568.346	499.244
AIC	898.409	649.206	502.283	433.18
chi2	914.657***	629.841***	707.291***	2077.824***
Pseudo_R2	0.257	0.29	0.251	0.341

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.

[a] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A3

Three-step IV results – M&A by SOEs (total and by type).

	(1) MA_TOT_pub	(2) MA_VER_pub	(3) MA_HOR_pub	(4) MA_CONGL_pub
Emergingi,t	0.955**	1.078**	0.938	0.503
	−2.29	−2.09	(1.46)	(0.90)
Pillar (only)$_{i,t}$	−0.064	0.479*	−0.126	−0.293
	(−0.21)	(1.65)	(−0.25)	(−1.03)
11th FYP	1.206**	0.696	1.62	−0.149
	(2.06)	(1.21)	(1.29)	(−0.45)
12th FYP	1.651***	1.404**	1.476	0.734*
	(2.76)	(2.29)	(1.07)	(1.73)
ROA$_{i,t}$	0.006	0.011*	0.013	0.01
	(1.14)	(1.65)	(1.33)	(1.36)
FIRMS$_{i,t}$	0.046**	0.016	0.02	0.040*
	(2.49)	(0.87)	(0.67)	(1.79)
LOSS_FIRMS_RATIO$_{i,t}$	0	−0.008**	−0.007	0.012
	(−0.09)	(−2.02)	(−1.43)	(1.50)
FIRMS_SIZE$_{i,t}$	−0.005	0.005***	−0.002	−0.007
	(−1.31)	(5.23)	(−0.63)	(−0.84)
DEBT_RATIOi,t	0.005	−0.014	0.04	0.007
	(0.17)	(−0.46)	(1.07)	(0.21)
SOE_RATEi,t	0.007	−0.015	0.023	0.017
	(0.45)	(−0.85)	(1.26)	(0.92)
PROD_GROWTH$_{i,t}$	0.393	0.377	0.224	0.783
	(0.86)	(0.67)	(0.54)	(1.02)
M&A_TOT_pub$_{i,t-1}$	0.063*			
	(1.79)			
M&A_VER_pub$_{i,t-1}$		0.051*		
		(1.65)		
M&A_HOR_pub$_{i,t-1}$			0.227	
			(1.60)	
M&A_CONGL_pub$_{i,t-1}$				0.053
				(0.30)
Cum_MA_y5$_{i,t}$	0.014***	0.016*	0.009*	0.017***
	(2.61)	(1.81)	(1.64)	(2.84)
OCMA	−0.641**	−0.09	−0.455	−0.785
	(−2.26)	(−0.28)	(−0.89)	(−1.48)
Constant	−4.507**	−3.180*	−7.860**	−5.942**
	(−2.50)	(−1.67)	(−2.57)	(−2.34)
Post 2008 dummy	Y	Y	Y	Y
N	360	360	360	360
Likelihood ratio test of alpha = 0[a]	154.00***	70.77***	37.40***	13.22***
Log-likelihood	−329.02	−236.838	−171.965	−125.337
BIC	758.104	573.74	443.993	350.737
AIC	692.04	507.676	377.929	284.673
chi2	193.665***	143.005***	344.020***	174.436***
Pseudo_R2	0.256	0.269	0.234	0.284

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.

[a] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A4
Robustness checks on political business cycle – negative binomial regressions.

	(1)	(2)	(3)	(4)
	$M\&A\_TOT_{i,t}$	$M\&A\_VER_{i,t}$	$M\&A\_HOR_{i,t}$	$M\&A\_CONGL_{i,t}$
$Emerging_{i,t,}$	1.168***	1.476***	0.910**	0.673**
	(3.05)	(4.08)	(2.19)	(2.15)
Pillar $(only)_{i,t}$[a]	0.235	0.212	0.293	−0.029
	(0.88)	(0.75)	(0.87)	(−0.13)
$ROA_{i,t}$	0.007	0.009*	0.006	0
	(1.35)	(1.79)	(1.12)	(0.08)
$FIRMS_{i,t}$	0.028	0.034*	0.01	0.039**
	(1.45)	(1.91)	(0.53)	(2.44)
$LOSS\_FIRMS\_RATIO_{i,t}$	−0.008*	−0.004	−0.006	0.112
	(−1.67)	(−0.98)	(−1.03)	(0.65)
$FIRMS\_SIZE_{i,t}$	0.004***	0.005***	0.002	−0.117
	(4.81)	(4.81)	(1.13)	(−0.63)
DEBT_RATIOi,t	−0.003	−0.005	−0.005	−0.005
	(−0.09)	(−0.16)	(−0.16)	(−0.20)
SOE_RATEi,t	0	−0.007	0.004	0.005
	(−0.02)	(−0.40)	(0.27)	(0.31)
$PROD\_GROWTH_{i,t}$	0.612	1.490**	1.283**	−0.379
	(1.17)	(2.29)	(2.09)	(−0.38)
$M\&A\_TOT_{i,t-1}$	0.071***			
	(4.02)			
$M\&A\_VER_{i,t-1}$		0.044*		
		(1.89)		
$M\&A\_HOR_{i,t-1}$			0.167***	
			(2.99)	
$M\&A\_CONGL_{i,t-1}$				0.125***
				(3.15)
$Cum\_MA\_y5_{i,t}$	−0.007	0.014*	0.010***	0.008**
	(−0.94)	(1.68)	(2.60)	(2.20)
CPC_YEAR	−0.898	−0.707	−0.781	−0.999
	(−1.59)	(−0.77)	(−1.04)	(−0.75)
CPC_AFTER	0.313	0.476	0.31	−0.099
	(0.57)	(0.50)	(0.45)	(−0.09)
CPC_BEFORE	−0.033	−0.015	0.224	0.24
	(−0.06)	(−0.02)	(0.27)	(0.18)
OCMA	−0.125	−0.161	−0.451	0.04
	(−0.38)	(−0.63)	(−0.95)	(0.17)
Constant	−2.369	−3.263*	−3.378**	−3.443**
	(−1.37)	(−1.85)	(−1.98)	(−2.08)
FYP dummies	Y	Y	Y	Y
Post 2008 dummy	Y	Y	Y	Y
Likelihood ratio test of alpha = 0[b]	0.096	0.054	0.034	−0.29
log-likelihood	(0.43)	(0.21)	(0.15)	(−0.93)
N	360	360	360	360
BIC	1264.847	939.395	789.994	748.781
AIC	1187.125	861.673	712.272	671.059
chi2	717.664***	593.444***	970.480***	986.041***
Pseudo_R2	0.219	0.25	0.243	0.285

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. All models are negative binomial with clustered standard errors.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A5
Robustness checks for controls simultaneity – Total M&A.

	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)
$Emerging_{i,t,}$	1.300***	0.923***	1.267***	0.775**	1.183***	0.815**
	(3.16)	(2.98)	(3.05)	(2.20)	(2.95)	(2.11)
Pillar $(only)_{i,t}$[a]	0.267	0.223	0.311	0.276	0.133	0.354
	(0.96)	(1.04)	(1.11)	(1.17)	(0.47)	(1.48)
$ROA_{i,t-1}$	0.005	0.002				
	(0.98)	(0.36)				
$ROA_{i,t-3}$			0.007	0.006		
			(1.12)	(0.96)		

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Table A5 (*continued*)

	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)	M&A_TOT (Negative binomial)	M&A_TOT (Poisson)
$ROA_{i,t-5}$					0.012 (1.35)	0.006 (0.91)
$FIRMS_{i,t-1}$	0.035 (1.58)	0.016 (1.23)				
$FIRMS_{i,t-3}$			0.034 (1.40)	0.002 (0.24)		
$FIRMS_{i,t-5}$					0.032 (1.12)	−0.002 (−0.13)
$LOSS\_FIRMS\_RATIO_{i,t-1}$	0.005 (1.27)	0.004 (1.48)				
$LOSS\_FIRMS\_RATIO_{i,t-3}$			−0.020*** (−4.11)	−0.012*** (−2.93)		
$LOSS\_FIRMS\_RATIO_{i,t-5}$					−0.009* (−1.78)	−0.008*** (−2.82)
$FIRMS\_SIZE_{i,t-1}$	0.003** (2.09)	0.003** (2.27)				
$FIRMS\_SIZE_{i,t-3}$			0.002 (1.49)	0.002 (1.32)		
$FIRMS\_SIZE_{i,t-5}$					−0.002** (−2.26)	−0.002* (−1.70)
$DEBT\_RATIO_{i,t-1}$	−0.01 (−0.29)	−0.002 (−0.07)				
$DEBT\_RATIO_{i,t-3}$			−0.009 (−0.25)	0.008 (0.32)		
$DEBT\_RATIO_{i,t-5}$					0.005 (0.13)	0.012 (0.47)
$SOE\_RATE_{i,t-1}$	−0.002 (−0.14)	0.005 (0.39)				
$SOE\_RATE_{i,t-3}$			−0.003 (−0.19)	0.004 (0.27)		
$SOE\_RATE_{i,t-5}$					−0.002 (−0.14)	0.004 (0.39)
$PROD\_GROWTH_{i,t}$	−0.28 (−0.70)	−0.348 (−1.35)	0.194 (0.47)	−0.171 (−0.66)	−0.18 (−0.45)	−0.225 (−0.78)
$M\&A\_TOT_{i,t-1}$	0.049*** (3.00)	0.034*** (4.05)	0.046** (2.35)	0.034*** (3.12)	0.060*** (3.03)	0.032** (2.55)
$Cum\_MA\_y5_{i,t}$	0.001 (0.08)	−0.003 (−0.69)	0.003 (0.30)	−0.002 (−0.29)	−0.005 (−0.63)	−0.001 (−0.11)
Constant	−2.024 (−1.02)	−2.427 (−1.55)	−2.027 (−0.95)	−2.954* (−1.68)	−2.421 (−0.94)	−2.784 (−1.56)
Dummies	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA
N	360	360	360	360	300	300
Likelihood ratio test of alpha = 0[b]	0.162		0.21		0.2	
log-likelihood	−578.335	−972.72	−581.197	−1011.342	−554.927	−981.947
BIC	1256.734	2039.618	1262.458	2116.863	1206.818	2055.155
AIC	1190.67	1977.44	1196.395	2054.685	1143.853	1995.895
chi2	1530.386***	2230.832***	983.369***	1992.608***	828.130***	1599.838***
Pseudo_R2	0.212	0.704	0.209	0.692	0.19	0.668

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. Only IV-third steps are reported. First steps confirm the instrument validity. They are omitted for the sake of conciseness and are available upon request.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A6

Robustness checks for controls simultaneity – Vertical M&A.

	M&A_VER (Negative binomial)	M&A_VER (Poisson)	M&A_VER (Negative binomial)	M&A_VER (Poisson)	M&A_VER (Negative binomial)	M&A_VER (Poisson)
$Emerging_{i,t,}$	1.487*** (4.17)	0.914*** (3.09)	1.479*** (3.79)	0.780** (2.45)	1.375*** (3.93)	0.914** (2.50)
Pillar $(only)_{i,t}$[a]	0.186 (0.67)	0.229 (0.99)	0.226 (0.81)	0.278 (1.14)	0.112 (0.41)	0.342 (1.51)
$ROA_{i,t-1}$	0.011* (1.93)	0.003 (0.46)				
$ROA_{i,t-3}$			0.013*	0.004		

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Table A6 (*continued*)

	M&A_VER (Negative binomial)	M&A_VER (Poisson)	M&A_VER (Negative binomial)	M&A_VER (Poisson)	M&A_VER (Negative binomial)	M&A_VER (Poisson)
			(1.89)	(0.54)		
ROA$_{i,t-5}$					0.022***	0.009
					(2.59)	(1.20)
FIRMS$_{i,t-1}$	0.034*	0.022				
	(1.75)	(1.42)				
FIRMS$_{i,t-3}$			0.037	0.014		
			(1.42)	(1.19)		
FIRMS$_{i,t-5}$					0.035	0.005
					(1.07)	(0.25)
LOSS_FIRMS_RATIO$_{i,t-1}$	−0.009**	−0.004				
	(−2.15)	(−0.99)				
LOSS_FIRMS_RATIO$_{i,t-3}$			−0.016***	−0.011***		
			(−3.89)	(−2.92)		
LOSS_FIRMS_RATIO$_{i,t-5}$					−0.006	−0.007**
					(−1.33)	(−2.19)
FIRMS_SIZE$_{i,t-1}$	0.004***	0.005***				
	(3.36)	(3.57)				
FIRMS_SIZE$_{i,t-3}$			0.004***	0.003**		
			(2.78)	(2.08)		
FIRMS_SIZE$_{i,t-5}$					−0.001	−0.001
					(−1.05)	(−0.81)
DEBT_RATIO$_{i,t-1}$	−0.006	0.002				
	(−0.18)	(0.08)				
DEBT_RATIO$_{i,t-3}$			−0.012	0.003		
			(−0.37)	(0.08)		
DEBT_RATIO$_{i,t-5}$					0.002	0.021
					(0.04)	(0.68)
SOE_RATE$_{i,t-1}$	−0.008	−0.006				
	(−0.47)	(−0.31)				
SOE_RATE$_{i,t-3}$			−0.009	−0.01		
			(−0.55)	(−0.55)		
SOE_RATE$_{i,t-5}$					−0.005	−0.004
					(−0.41)	(−0.32)
PROD_GROWTH$_{i,t}$	0.304	−0.22	0.934**	−0.124	0.773	−0.15
	(0.66)	(−0.62)	(1.96)	(−0.26)	(1.58)	(−0.36)
M&A_VER$_{i,t-1}$	0.029	0.074***	0.019	0.071***	0.028	0.072***
	(1.31)	(3.85)	(0.89)	(3.48)	(1.23)	(4.63)
Cum_MA_y5$_{i,t}$	0.017*	−0.004	0.019**	−0.003	0.015*	−0.003
	(1.89)	(−0.81)	(2.22)	(−0.55)	(1.77)	(−0.72)
Constant	−3.392*	−3.645*	−2.981	−3.431	−3.252	−4.059**
	(−1.81)	(−1.84)	(−1.46)	(−1.59)	(−1.33)	(−1.98)
Dummies						
N	360	360	360	360	300	300
Likelihood ratio test of alpha = 0[b]	0.076		0.139		0.137	
log-likelihood	−410.606	−584.852	−413.929	−608.71	−399.668	−582.526
BIC	921.275	1263.881	927.922	1311.597	896.301	1256.312
AIC	855.212	1201.703	861.859	1249.42	833.337	1197.052
chi2	536.940***	1002.972***	483.778***	1017.729***	546.891***	2381.750***
Pseudo_R2	0.25	0.673	0.244	0.66	0.224	0.643

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. Only IV-third steps are reported. First steps confirm the instrument validity. They are omitted for the sake of conciseness and are available upon request.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A7

Robustness checks for controls simultaneity – Horizontal M&A.

	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)
Emerging$_{i,t,}$	1.111**	1.149**	1.233***	1.261**	1.122**	1.220**
	(2.39)	(2.49)	(2.59)	(2.25)	(2.55)	(2.21)
Pillar (only)$_{i,t}$[a]	0.34	0.23	0.421	0.371	0.261	0.474
	(0.94)	(0.66)	(1.13)	(0.93)	(0.74)	(1.13)
ROA$_{i,t-1}$	0.002	0.004				
	(0.36)	(0.57)				
ROA$_{i,t-3}$			0.005	0.008		
			(0.61)	(0.98)		

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Table A7 (*continued*)

	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)	M&A_HOR (Negative binomial)	M&A_HOR (Poisson)
$ROA_{i,t-5}$					0.006	0.004
					(0.58)	(0.33)
$FIRMS_{i,t-1}$	0.023	0.022				
	(1.12)	(1.46)				
$FIRMS_{i,t-3}$			0.012	0.008		
			(0.53)	(0.54)		
$FIRMS_{i,t-5}$					0.014	0.01
					(0.54)	(0.47)
$LOSS\_FIRMS\_RATIO_{i,t-1}$	0.014***	0.012***				
	(3.38)	(3.59)				
$LOSS\_FIRMS\_RATIO_{i,t-3}$			−0.016***	−0.011**		
			(−2.95)	(−2.41)		
$LOSS\_FIRMS\_RATIO_{i,t-5}$					−0.015***	−0.010**
					(−2.74)	(−2.09)
$FIRMS\_SIZE_{i,t-1}$	−0.001	−0.001				
	(−0.42)	(−0.39)				
$FIRMS\_SIZE_{i,t-3}$			0	0		
			(0.29)	(0.19)		
$FIRMS\_SIZE_{i,t-5}$					−0.003	−0.003
					(−1.12)	(−1.17)
$DEBT\_RATIO_{i,t-1}$	−0.022	−0.001				
	(−0.65)	(−0.03)				
$DEBT\_RATIO_{i,t-3}$			−0.017	0.008		
			(−0.52)	(0.27)		
$DEBT\_RATIO_{i,t-5}$					−0.007	−0.001
					(−0.20)	(−0.02)
$SOE\_RATE_{i,t-1}$	0	0.014				
	(0.00)	(0.94)				
$SOE\_RATE_{i,t-3}$			−0.001	0.013		
			(−0.10)	(0.84)		
$SOE\_RATE_{i,t-5}$					0.001	0.01
					(0.10)	(0.73)
$PROD\_GROWTH_{i,t}$	0.555	0.56	0.703**	0.595	0.659*	0.616*
	(1.58)	(1.60)	(2.27)	(1.52)	(1.84)	(1.65)
$M\&A\_HOR_{i,t-1}$	0.156***	0.022	0.165***	0.027	0.161***	0.025
	(2.62)	(0.69)	(2.85)	(0.84)	(2.82)	(0.74)
$Cum\_MA\_y5_{i,t}$	0.010***	0.009**	0.008**	0.008**	0.009**	0.009***
	(2.71)	(2.43)	(2.26)	(2.20)	(2.18)	(2.61)
Constant	−2.126	−3.672*	−2.477	−4.333*	−2.809	−3.557
	(−1.02)	(−1.80)	(−1.15)	(−1.88)	(−1.16)	(−1.35)
Dummies						
N	360	360	360	360	300	300
Likelihood ratio test of alpha = 0[b]	0.174		0.194		0.211	
log-likelihood	−339.836	−435.588	−340.435	−440.44	−328.998	−433.659
BIC	779.735	965.354	780.933	975.057	754.961	958.579
AIC	713.672	903.176	714.869	912.879	691.997	899.318
chi2	486.069***	1357.371***	417.359***	561.500***	262.952***	486.900***
Pseudo_R2	0.234	0.532	0.233	0.527	0.21	0.49

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. Only IV-third steps are reported. First steps confirm the instrument validity. They are omitted for the sake of conciseness and are available upon request.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

Table A8

Robustness checks for controls simultaneity – Conglomerate M&A.

	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)
$Emerging_{i,t,}$	0.717**	0.558*	0.662*	0.448	0.652**	0.411
	(2.06)	(1.71)	(1.88)	(1.25)	(2.15)	(1.12)
Pillar (only)$_{i,t}$[a]	−0.062	−0.055	−0.017	0.001	−0.004	0.048
	(−0.25)	(−0.23)	(−0.06)	(0.00)	(−0.02)	(0.19)
$ROA_{i,t-1}$	−0.002	−0.003				
	(−0.37)	(−0.69)				
$ROA_{i,t-3}$			0.002	−0.001		
			(0.29)	(−0.23)		
$ROA_{i,t-5}$					0.002	−0.002

(*continued on next page*)

Table A8 (*continued*)

	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)	M&A_CONGL (Negative binomial)	M&A_CONGL (Poisson)
					(0.27)	(−0.33)
$FIRMS_{i,t-1}$	0.047***	0.039***				
	(2.71)	(3.16)				
$FIRMS_{i,t-3}$			0.036*	0.023**		
			(1.91)	(2.12)		
$FIRMS_{i,t-5}$					0.039	0.025
					(1.64)	(1.62)
$LOSS\_FIRMS\_RATIO_{i,t-1}$	0.014	0.009				
	(0.77)	(1.32)				
$LOSS\_FIRMS\_RATIO_{i,t-3}$			0.028	0.004		
			(0.23)	(0.30)		
$LOSS\_FIRMS\_RATIO_{i,t-5}$					0.135	0.019
					(0.90)	(0.19)
$FIRMS\_SIZE_{i,t-1}$	−0.019	−0.008				
	(−0.92)	(−1.16)				
$FIRMS\_SIZE_{i,t-3}$			−0.046	−0.016		
			(−0.36)	(−1.08)		
$FIRMS\_SIZE_{i,t-5}$					−0.166	−0.038
					(−1.03)	(−0.35)
$DEBT\_RATIO_{i,t-1}$	−0.004	0.003				
	(−0.13)	(0.12)				
$DEBT\_RATIO_{i,t-3}$			0.003	0.011		
			(0.08)	(0.41)		
$DEBT\_RATIO_{i,t-5}$					0.007	0.012
					(0.24)	(0.46)
$SOE\_RATE_{i,t-1}$	0.002	0.011				
	(0.14)	(0.81)				
$SOE\_RATE_{i,t-3}$			0	0.009		
			(0.03)	(0.63)		
$SOE\_RATE_{i,t-5}$					0.001	0.008
					(0.08)	(0.62)
$PROD\_GROWTH_{i,t}$	−0.641*	−0.172	−0.627*	−0.213	−0.47	−0.084
	(−1.66)	(−0.50)	(−1.83)	(−0.63)	(−1.29)	(−0.24)
$M\&A\_VER_{i,t-1}$	0.096**	0.058*	0.107***	0.068**	0.103***	0.070**
	(2.38)	(1.77)	(2.68)	(2.00)	(2.96)	(2.18)
$Cum\_MA\_y5_{i,t}$	0.008*	0.006	0.007	0.005	0.007*	0.006
	(1.90)	(1.30)	(1.51)	(1.06)	(1.84)	(1.07)
Constant	−3.512**	−4.091***	−3.451*	−4.284**	−3.408*	−4.024**
	(−2.20)	(−2.60)	(−1.84)	(−2.34)	(−1.72)	(−2.02)
Dummies	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA	Post 2008, FYP, OCMA
N	360	360	360	360	300	300
Likelihood ratio test of alpha = 0[b]	−0.244		−0.15		−0.142	
log-likelihood	−320.819	−362.692	−322.006	−371.973	−315.319	−366.365
BIC	741.702	819.562	744.076	838.124	727.602	823.99
AIC	675.638	757.384	678.012	775.946	664.638	764.73
chi2	583.848***	1353.517***	483.150***	1150.273***	258.223***	555.436***
Pseudo_R2	0.273	0.627	0.27	0.618	0.247	0.588

Source: authors' elaboration. T-statistics in brackets. Significance levels: * 10%, ** 5%, *** 1%. Only IV-third steps are reported. First steps confirm the instrument validity. They are omitted for the sake of conciseness and are available upon request.

[a] The dummy "Pillar" is omitted in the first step due to collinearity.

[b] The likelihood ratio test of alpha = 0 is obtained by negative binomial regressions without clustered standard errors.

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