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State-Owned Enterprises as Innovation Leaders

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Abstract

In this paper, I test the impact of state ownership on innovation; input, efficiency and output. I use ORBIS ownership data of companies in Europe, (South-)East Asia and Brazil and find that the impact is non-linear and highly circumstantial. The impact depends on corruption levels and technology intensity of the sector. State-owned enterprises in corrupt nations are able to use their political connections to acquire more innovation input, but suffer from efficiency problems. In technology intensive sectors, state-owned enterprises are able to outperform their peers due to their superior risk-taking abilities. Finally, I find evidence that state ownership has an inverted U-shaped impact on innovation output.

Keywords: State ownership, innovation

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1. Introduction

"State-owned enterprises are a key force in the national technological innovation system and shoulder important responsibilities in key core technological innovations related to the long-term development of the country (China)." - Wu Weihua, Vice Chairperson of the 13th National People's Congress Standing Committees (Teller Report, 2020).

In the 80s and start of the 90s, the world saw a massive wave of privatization as many countries embraced liberalism and globalization. Under the leadership of Ronald Reagan in the United States and Margaret Thatcher in Western Europe, a more laissez-faire policy was adopted in the economies of many Western nations (Poole, 2004). People, such as Reagan (1987) argued that: "Freedom of enterprise at an individual level builds countries from the bottom up. A lack of it, on the other hand, has the opposite effect." Privatization, in his opinion, led to more efficiency, competition, a reduction of the country's deficit and more innovation (Henig, 1989). After the collapse of communism at the end of the 80s, privatization of firms further increased as many nations in Eastern Europe started to adopt a capitalistic system. In the former Soviet-Union the oil industry, once the economic lifeblood of communism, was privatized in 1994 (Semikolenova & Berkowitz, 2006).[1] The World Bank reported that over 45,300 medium and large-sized enterprises together with hundreds of thousands of small enterprises were privatized in the early 90s in Eastern Europe alone (Nellis, 1996). Many people thought that the role of State-Owned Enterprises (SOEs) was played out. However, in recent years the economic importance and influence of SOEs has increased again, mainly due to the economic growth of China. In the last two decades, the percentage of assets of the 2,000 largest firms belonging to SOEs increased from five to twenty percent. These large SOEs operate around the world and are mostly located in Europe and East-Asia (International Monetary Fund, 2020).

A significant amount of research, both theoretical and empirical, has been put into the performance of SOEs. Most researchers agree that SOEs generally underperform compared to their private peers.[2] In a recent report the IMF (2020) warns of the impact underperforming SOEs can have on both economic and societal goals. States often create SOEs with a mandate to meet specific goals, such as water provision and electricity. When these SOEs fail due to underperformance, it leaves millions without drinking water and electricity. The IMF further points out that public banks financing these SOEs often neglect their mandate, promoting

[1] Although legislation was passed giving the Russian government significant control in private oil companies.
[2] See for example the papers of Boardman & Vining (1989), Shleifer (1998), Stan, Peng & Bruton (2014), and Musacchio, Lazzarini, & Aguilera (2015) on SOE underperformance.

economic development, and take excessive risks leaving the economy vulnerable to crises. In emerging economies, states are often unable to effectively monitor SOEs. Consequently, SOEs can build up large and hidden debts which, if they need to be bailed out by the state, costs the taxpayer in some cases more than 10 percent their nations GDP.

Even though SOEs seem to be economically less efficient than their private peers, they make up half of the gross world product, around 45 trillion US dollar. An amount that is still growing today. Recent studies have tried to explain why still so many SOEs exist, by looking into the positive sides of SOEs. SOEs can focus less on profits and more on societal goals; studies show that SOEs engage more in environmental issues (Hsu, Liang & Matos, 2018), provide more employment (Rama & Belser, 2001), are more committed to corporate social responsibility goals (Córdoba-Pachón, Garde-Sánchez & Rodríguez-Bolívar, 2014) and can innovate more (Belloc, 2014) compared to Privately-Owned Enterprises (POEs). This last point, the positive impact of state ownership on innovation, has gained increasing attention with the rise of China and its state-sponsored innovation programs (Hsu, 2016). Chinese president Xi Jinping has repeatedly expressed his strong support for SOEs as drivers of innovation (Mercator Institute for China Studies, 2020). Also in other nations and institutions, such as the European Union, the role of SOEs as innovation drivers has become a topic of discussion (Sturesson, McIntyre & Jones, 2015).

So are SOEs indeed better innovators than POEs? Firstly, SOEs can acquire more innovation resources. Studies have pointed out unambiguously that SOEs are significantly more likely to receive loans from state banks (Claessens, Feijen & Laeven, 2008; Boubakri & Saffar, 2019), receive those loans at a lower cost (Khwaja & Mian, 2005) and get bailed out more by state banks (Faccio, Masulis & McConnell, 2006), meaning that the cost of capital is significantly lower for SOEs. This does not mean that SOEs are good for society as a whole. Indeed most researchers point out the opposite; SOEs often spend the resources inefficiently (Nguyen & Van Dijk, 2012). However, this does mean that governments can help SOEs acquire more resources needed for innovation, especially if the financial sector of a certain nation is underdeveloped and enterprises rely on the government for financing (Musacchio, Lazzarini, & Aguilera, 2015). Secondly, SOEs can take on more risk, since they are less likely to go bankrupt and care less about profit-maximization than POEs (Faccio et al., 2006; Chen, Lee & Li, 2008). Additional risk-taking means SOEs can take on more risky, but good projects (Belloc, 2014). However the picture is not as unambiguous as it might seem at first glance; SOEs also face innovation issues. Zhou, Gao & Zhao (2017) point out that state ownership is associated with inefficiency problems, i.e., high agency costs, which harms innovation output of SOEs.

Since it is unclear which effect dominates, I will test in this paper what the exact impact of state ownership is on innovation. Understanding the impact of state ownership on innovation can greatly impact government policy. It can help states better decide, if and in what situations, it is desirable to privatize or nationalize certain enterprises. In their recommendations for future research, Inoue et al. (2013) point out that research on the impact of state ownership on innovation is still limited. Most studies focus solely on Chinese SOEs and fail to take the non-linear relation between state ownership and innovation into account. In this study I use novel ORBIS ownership data, to gain a worldwide sample and investigate this non-linear relation. Considering the limited amount of research on this topic and the significant impact privatization and nationalization can have on economic and societal goals, it is an interesting subject to research.

To coherently answer what the impact of state ownership on innovation is, I firstly review literature on this topic and formulate three hypotheses. Secondly, I discuss my dataset and give descriptive statistics. The empirical part of the paper consists of two parts. In the first part, I test the effect of SOEs on innovation by using a SOE dummy and directly compare SOEs to POEs in different empirical contexts, i.e., highly corrupt nations and high-tech sectors.[3] In the second part, I use a different method to measure the impact of state ownership. I compute and use a continuous state ownership variable, to investigate the non-linear impact of state ownership on innovation.[4] Lastly, I answer the research question, give a conclusion and discuss recommendations for future research.

2. Literature review and hypotheses

2.1 Innovation input

Earlier studies have found that government connections give SOEs access to more and cheaper capital (Claessens et al., 2008; Boubakri & Saffar, 2019; Khwaja & Mian, 2005). These results fit in with the institutional-based view. This view argues that state capital, guarantees and resources can fill certain institutional voids. This is especially the case in emerging economies where financial markets are underdeveloped, where there are skilled labor shortages and where there are high levels of corruption (Musacchio et al., 2015). In markets with large institutional voids, the performance of SOEs relative to POEs significantly improves (Peng,

[3] Similar to earlier studies of e.g. Faccio (2006), Claessens et al. (2008), Ayyagiri, Demirgüç-Kunt & Maksimovic (2011) and Hsu et al. (2018).
[4] The use of a continuous state ownership variable builds on earlier papers of Inoue, Lazzarini & Musacchio (2013) and Zhou et al. (2017).

Wang & Jiang, 2008). Inoue et al. (2013) find, using data from Brazil, that companies with the state as a minority investor outperform their competitors since they are less affected by agency distortions compared to full-fledged SOEs and have access to cheap capital. This outperformance is most significant in sectors where companies have latent investment opportunities, but severe constraints on accessing external capital. These results suggest that SOEs, due to state connections and government help, have an advantage over POEs in acquiring innovation resources. These additional resources allow them to exercise the latent investment opportunities and outperform their peers.

Further research on the effect of state capital on innovation is scarce. In the limited research that has been done, Aghion, Van Reenen & Zingales (2013) find that the presence of institutional investors in a certain firm positively affects innovation. Belloc (2014) and Zhou et al. (2017) further elaborate on innovation in SOEs. The researchers give several reasons why SOEs have an advantage in innovation. Innovation requires significant resources, mainly skilled labor and financial resources (innovation input).[5] In emerging markets, access to these resources can be limited and is mostly controlled by the state (Musacchio & Lazzarini, 2014; Zhou et al., 2017). As mentioned before, SOEs are significantly more likely to receive loans from state banks (Claessens et al., 2008; Boubakri & Saffar, 2019) and receive these loans at a substantially lower cost than their peers (Khwaja & Mian, 2005). Belloc (2014) also points out that states can and do impose reduced mandatory payments, such as taxes, for the financing of innovative projects of SOEs. Chen et al. (2008) further find, by using evidence from China, that SOEs disproportionality profit from government subsidies. The same researchers argue that SOEs can take on more financial risk than their peers, because they care less about profit maximization. Moreover, when companies take on too much risk, the damage is smaller for SOEs. They are more likely to receive a bailout due to their political connections (Faccio et al. 2006). Furthermore, weak intellectual property law and legal actions significantly limit innovative activity. Firms with political connections face less legal actions, get lower penalties and are more likely to win legal cases, giving SOEs more incentive to innovate (Correia, 2014). It is therefore reasonable to argue that SOEs have higher innovation input than POEs, since they have a lower cost of capital, can take more financial risks and face less litigation risk, i.e., patent infringement complaints.

Hypothesis 1a: State ownership is positively related to innovation input.

[5] In this paper, I will focus on the financial side, i.e., R&D expenditures.

Yearly, more than 1 trillion US dollar in bribes is paid according to the World Economic Forum. Corruption costs more than 5% of global GDP (Castro, Phillips & Ansari, 2020). However, curiously, corruption could actually give SOEs an advantage in innovation input relative to POEs. SOEs perform better, when corruption is higher. Stocks of SOEs in countries with high levels of corruption generate significant abnormal returns of 4.32%, while in countries with low levels of corruption there is no significant outperformance (Faccio, 2006). More specifically on innovation, Xu & Yano (2017) find that anti-corruption actions in China led to an increase in innovation input. This increase was only observed in POEs, meaning that SOEs originally had relatively high innovation input compared to POEs. Their findings can be explained by the institutional-based view. Corruption leads to several institutional voids; e.g. an inefficient financial system, (Venard & Hanafi, 2008; McFarlane, 2001) and weaker law enforcement (Fijnaut & Huberts, 2012). State connections can help SOEs fill these institutional voids and outperform their private peers in certain areas (Musacchio et al., 2015). In countries with high corruption, SOEs are better able to use their political connections to gain more resources for innovation.

However, contradictory, research in Denmark, the least-corrupt nation in the world according to the Corruption Perceptions Index (CPI), shows that political connections lead to a lower cost of capital and can boost company operating returns in a low-corrupt country (Amore & Bennedsen, 2013). As such, it is not unreasonable to argue that political connections can also boost innovation input in low-corrupt countries. Therefore, it is an interesting hypothesis to test.

Hypothesis 1b: Higher corruption levels further increase innovation input of SOEs.

2.2 Innovation efficiency

Even though SOEs might have more innovation input, it is unclear if this input is converted in actual output. Shleifer (1998) argues that POEs have more incentive to innovate and use their resources more efficiently. Harts (1995) theory of incomplete contracts is used to explain this difference. In a basic setting, POEs have more incentive to effectively innovate, since the owner of a private firm reaps more benefits from the innovations; in SOEs the inventor has to reach an agreement with the owner (the state) to implement the innovation and therefore shares the benefits with the owner.

This idea is in accordance with the agent-principal problem or agency view (Zhou et al., 2017). The agent view states that the goals of the agent (the manager), who cares about his own utility, and the principal (the shareholder), who cares about shareholder value, are not aligned

(Eisenhardt, 1989). As such, the manager has little incentive to efficiently innovate, or run the firm efficiently in general. Principals of POEs are more than SOEs able to limit this problem by designing better performance-based contracts (Shirley & Nellis, 1991; Bai & Xu, 2005) and creating effective monitoring systems (Uddin & Tsamenyi, 2005). SOEs are monitored worse, because it is hard to identify a single principal. Since the state owns the company, the principal is us all; the society. It can therefore be difficult to align the positions of the agent and the principal (Shleifer, 1998; Belloc 2014). Citizens often lack the necessary monitoring mechanism. As such, government officials can use SOEs to advance their own personal and political goals, which reduces innovation efficiency (Zhou et al., 2017).

SOEs also have an advantage in regard to innovation efficiency. Belloc (2014) highlights the role of a state as a knowledge network leader. Since companies tend to cooperate more with companies who have the same shareholder (Miozzo & Dewick, 2002), and since the state is the biggest shareholder in most countries, SOEs can more easily set up inter-firm projects. The knowledge network leader will not be specifically explored in this paper, and instead the focus will be on the agent-principal problem.

Hypothesis 2a: State ownership negatively impacts innovation efficiency.

In a recent working paper, the IMF warns for the negative impact of corruption. They find persuasive evidence that corruption undermines the performance of SOEs (Baum, Hackney, Medas & Sy, 2019). Looking more specifically at innovation, the same argument seems to hold. In environments with more corruption, it is easier for government officials to use SOEs for their personal gains. Therefore, the agency problem will be larger and innovation efficiency will decrease (Groenendijk, 1997). Moreover, managers of SOEs in corrupt states are often not appointed based on their capabilities, but based on their political affiliation. These managers often lack the capabilities to innovate efficiently (Zhou et al., 2017).

Also, these managers are inclined to pursue goals of the political party and not the goals of the company (Fan, Wong & Zhang, 2007). This last point does not necessarily lead to less innovation, this effect is country specific. For example, in China president Xi Jinping has made innovation-driven development government policy (Reuters, 2016; Zhao, 2016).

Hypothesis 2b: Corruption enhances the negative impact of state ownership on innovation efficiency.

When people think of industries in which SOEs are active, they mostly point out non-innovative sectors, such as mining, utilities and infrastructure. However, SOEs also play a role in innovative, high-technology sectors. SOEs are quite common in sectors, such as aerospace, shipbuilding, automotive industries, and industries linked to the military-industrial complex (Meissner, Sarpong & Vonortas, 2019). One of the goals of this paper is to help governments better decide, when privatization is the preferred option. One of the circumstances that could impact the effect of state ownership on innovation is sector innovativeness.

So why would SOEs perform significantly better in high-tech sectors? As explained earlier, SOEs can take on significantly more risk than POEs, which allows them to take on risky, but valuable innovative projects. The idea that this excess risk leads to better innovation in innovative sectors is not one from the political finance field, but from a different finance field: behavioral finance. In their behavioral finance paper, Hirshleifer, Low & Teoh (2012) discuss how overconfidence leads to more risk taking and helps CEOs (and the companies) to exploit innovative growth opportunities in innovative sectors. They argue that: "rational managers may, from the viewpoint of shareholders, excessively prefer the "D" in R&D—fairly reliable projects rather than risky but more promising innovative ones.'' The researchers indeed find evidence that overconfidence and the resulting additional risk taking positively impacts innovation and firm value in, and only in innovative, high-tech sectors. In their papers, Chen et al. (2008) and Belloc (2014) point out the positive effect excess risk taking by SOEs has on innovation. They note that SOEs can engage with uncertainty to an extent to which POE cannot, and as such have a comparative advantage in dealing with risky innovative projects. This advantage is expected to be most pronounced in sectors with abundant risky innovative projects, high-tech sectors.

Rather than focus on the risk argument, Zhou et al. (2017) point out that the agency problem is limited in high-tech sectors. Competition is generally higher in these sectors compared to other sectors the government is active in. As such, there are more benchmarks for evaluating SOE performance, making monitoring easier. Moreover, in high-tech markets the likelihood of bankruptcy is significantly increased as inefficient firms are quickly forced out of the market (Ayyagiri et al. 2011). As such, there is little room for government officials to use SOEs for personal gain. Therefore, it is expected that innovation efficiency of SOEs significantly improves in high-tech industries compared to non-high-tech sectors.

Hypothesis 2c: The negative effect of state ownership on innovation efficiency is smaller in high-technology sectors.

2.3 Non-linear effects of state ownership on innovation

As stated in the introduction, the paper is divided into two parts. In the second part, I look at the non-linear impact of state ownership on innovation. Again, the same two important theories are at play when looking at innovation in SOEs: the institutional-based view and the agency view. The institutional-based view points out that the state connections of SOEs can help them fill institutions voids and give SOEs access to scarce but needed resources for innovation. Interestingly, minority state-owned firms already benefit significantly from state connections and can more easily obtain financial resources than private firms (Musacchio & Lazzarini, 2014). However, there seems to be little additional benefits for wholly-owned SOEs (Musacchio et al., 2015). As such, a higher degree of state ownership should be associated with higher innovation input, however the increase in innovation input is marginally decreasing.

Hypothesis 3a: The impact of state ownership on innovation input is positive and marginally decreasing for higher levels of state ownership.

The agency view on the other hand states that state connections lead to efficiency problems which harms innovation. This problem is limited in firms with the state as a minority investor (Musacchio et al. 2015). Inoue et al. (2013) indeed find that in Brazil minority state-owned firms are hardly affected by the agency problem and as such have higher returns on assets and on capital expenditures. On the other hand, wholly and majority owned SOEs suffer significantly from agency problems. So, state ownership is negatively associated with innovation efficiency and this negative impact seems to be exponentially increasing.

Hypothesis 3b: The impact of state ownership on innovation efficiency is negative and exponentially increasing for higher levels of state ownership.

Zhou et al. (2017) research the combined effect of the institutional-based view and the agency view. They find, using data of Chinese SOEs, that the effect of state ownership on innovation output takes an inverted U-shape. In China, firms with 29.18 percent state ownership have the largest innovation output. As the state acquires a larger stake than 29.18 percent in the company, the growing agency problem starts to negatively affect innovation output more than the positive impact of additional innovation input. The opposite is the case when the states invest less than 29.12 percent; the effect of the decrease in the agency problem is not big enough to offset the effect of decreased innovation input. In this paper a similar inverted U-shaped relation between state ownership and innovation output is expected to be found when investigating worldwide data.

Hypothesis 3c: There exists an inverted U-shaped relation between state ownership and innovation output.

3. Data

The main dataset used in this paper is compiled from the ORBIS (BvD) database. The dataset consists of 819,666 companies in Europe, East Asia, South-East Asia and Brazil and uses data from the years 2011 to 2019. These regions are chosen, because a majority of the SOEs are located there (IMF, 2020). As such, most research focuses on SOEs in these regions, since they provide a rich source of information (Ayyagari et al., 2011). ORBIS defines SOEs as "organizations ultimately owned or de facto controlled by public sector entities".

To limit the number of issues with the dataset, I make several adjustments. Firstly, in line with recommendations of SOE research by the IMF, I focus on domestically-owned SOEs. This way I limit endogeneity issues (Baum et al., 2019). I drop all SOEs whose location of the Global Ultimate Owner (GUO) and Immediate Shareholder (ISH) does not match with the location of the Domestic Ultimate Ownership (DUO).[6]

Furthermore, I use the cleaning procedure recommended by Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych and Yesiltas (2015) to gain representative firm level data in ORBIS. For both SOEs and POEs, duplicates with the same identifier and year; observations with missing years; company-years with missing information on patent data, ownership data, firm financial statements and Tobin's Q are dropped. I also exclude companies with a negative amount of total assets in any year. Lastly, I only use enterprises with an 'active' status.

For testing the non-linear impact of state ownership, the amount of state ownership is computed by adding all public sector entity shareholders within a firm together. ORBIS reports both direct and total (indirect) shareholdings of individual shareholders. Naturally, the 'total' variable is preferred since it better reflects the influence of the state in a certain company. However, in a few cases the 'total' variable has some missing data. In those cases, the largest computed state ownership of either the 'direct' or the 'total' variable is taken into account. This method is in line with other SOE studies using ORBIS data (European Commission, 2018). Furthermore, I drop firms if the highest state ownership amount of either the 'direct' or 'total' variable is below the 50 percent, but the DUO of the firm is nevertheless reported by ORBIS to be a public sector entity, since it signals that the ownership data is incomplete for that particular enterprise.

After the cleaning procedure, I end up with 16,067 observations in the first part of the study. In the second part of the study, the dataset is slightly smaller and has 11,945 observations. The

[6] For simplicity reasons SOEs located in special administrative regions (e.g. Hongkong) are treated as if they were located in the country, where the central government is located (e.g. mainland China).

total amount of SOEs is 1,838 representing 22.90% of the total firms in the dataset. The SOEs are divided over 36 countries.[7]

3.1 Skewness, kurtosis and outliers

I use z-scores to cope with outliers. Bakker and Wicherts (2014) find that most researchers define a datapoint as an outlier, when the z-score is higher than | 3.29 |. This amount is based on research by Tabachnick and Fidell (2001). Z-scores can only be used, when the dataset is large enough, since z-scores will never exceed a certain score if a dataset is too small (Shiffler, 1988). I find that I can use the z-score of | 3.29 | for all my tests, using formula 1.

$$(1)\quad \text{Maximum z-score} = (n - 1)/\sqrt{n}$$

To further deal with skewness and kurtosis, I use the natural logarithm of my variables. Therefore, I drop datapoints with negative values, since the logarithm of a negative value is undefined. Only three datapoints have a negative value and as such, the impact of dropping them is negligible. Lastly, to reduce the influence of skewness, robust regressions are used (Leroy & Rousseeuw, 1987).

To empirically test whether my variables follow a normal distribution, I perform a Shapiro-Francia (SF) test. The SF test tests the null hypothesis that the data follow a normal distribution. It is the most powerful conventional test for testing normality, and contrary to the more used Shapiro-Wilk test, works with large data samples of up to 5,000 observations (Ahmad & Khan, 2015). The test statistic (W') is computed with formula 2.

$$(2)\quad W' = \frac{\left[\sum_{i=1}^{n} m_i X_{(i)}\right]^2}{\sum_{i=1}^{n} \left(X_{(i)} - \bar{X}\right)^2}$$

As such, the test depends on a vector of standard normal ordered statistics (m_i), the *i*th largest order statistic (X_i) and the sample mean ($\bar{X}$). When the data follow a normal distribution, W' will be close to one. The stronger the data deviate from a normal distribution, the smaller W' will be (Shapiro & Francia, 1972). To test whether my variables follow a normal distribution, I perform the SF test on data of 2019, because otherwise the results would suffer from time trends and the data sample would violate the maximum number of 5,000 observations.

[7] See table A1 in appendix A for the list of SOEs per country.

3.2 Descriptive statistics

3.2.1 Dependable variables

Innovation input: to proxy innovation input, I take the R&D expenditures of a certain company relative to the firm's total sales (Zhou et al., 2017). R&D expenditures are in thousands of US dollars. Despite my proxy being a ratio, it suffers from high skewness and kurtosis. Furthermore, the null hypothesis that the data follow a normal distribution is rejected. As such, it is hard to interpret the results in the first three columns. Therefore, I erase twelve outliers and take the natural logarithm. Afterwards, skewness and kurtosis decrease. This time the distribution resembles a normal distribution significantly more.[8] The normal distribution can no longer be rejected using a 95% confidence level. In my sample, innovation input of SOEs is slightly smaller than innovation input of POEs (columns 4 and 5).

Table 1a Descriptive statistics of innovation input in the period of 2011-2019.[9]

	Innovation input$_{a,t}$ (non-logarithmic)			Innovation input$_{a,t}$ (logarithmic)		
	(1)	(2)	(3)	(4)	(5)	(6)
	POE	SOE	All firms	POE	SOE	All firms
Observations	12,788	3,319	16,107	12,776	3,795	16,095
Minimum	.000	.000	.000	-16.613	-10.807	-16.613
Maximum	7.937	.151	7.292	1.987	-1.890	1.987
Mean	.039	.033	.038	-4.353	-4.446	-4.375
Median	.020	.004	.017	-4.077	-5.486	-4.098
Std. Deviation	.156	.024	.135	1.709	1.956	1.714
Skewness	31.337	3.105	31.491	-.856	-.323	-.839
Kurtosis	1255.397	13.450	1277.958	4.473	3.280	4.404

Table 1b Shapiro-Francia test on innovation input.

	Innovation input$_a$ (non-logarithmic)	Innovation input$_a$ (logarithmic)
W'	.641***	.965*

** p < .100; ** p < .050; *** p < .010*

Innovation efficiency: I come up with a novel proxy for innovation efficiency. I measure innovation efficiency by taking the firms pending patents as a proxy for patent growth and divide it by its one year-lagged R&D expenditures. The ORBIS database only provides patent

[8] See figure B1 in appendix B for the distribution plot.

[9] Note that throughout this paper, subscripts are added to the end of each variable, an *a* means that the variable is company specific, *t* time specific, *i* industry specific and *c* country specific.

data of 2019. I use the one-year lagged R&D expenditures, since it takes on average one year for R&D expenditures to produce a patent (Danguy, De Rassenfosse & van Pottelsberghe de la Potterie, 2010). The median amount of R&D expenditure it takes to produce a patent is 51,714.60 US dollar.[10] I drop one outlier and a datapoint with a negative value, since a logarithm of a negative number is undefined. After taking the logarithm and dropping the outlier, skewness and kurtosis significantly decrease.[11] Using the SF test, I cannot reject the null hypothesis that the data follows a normal distribution. In my dataset, POEs on average are more efficient in innovating than SOEs (column 4 and 5).

Table 2a Descriptive statistics of innovation efficiency in 2019.

	Innovation efficiency$_a$ (non-logarithmic)			Innovation efficiency$_a$ (logarithmic)		
	(1)	(2)	(3)	(4)	(5)	(6)
	POE	SOE	All firms	POE	SOE	All firms
Observations	1,114	300	1,414	1,112	300	1,412
Minimum	-.068	.000	-.068	-10.125	-9.017	-10.125
Maximum	513.848	.894	513.848	1.984	-.112	1.984
Mean	.440	.392	.435	-4.022	-4.215	-4.047
Median	.020	.014	.019	-3.919	-4.322	-3.946
Std. Deviation	13.814	.162	13.666	1.630	1.680	1.642
Skewness	37.136	5.157	37.537	-.318	.227	-.313
Kurtosis	1380.692	27.747	1410.656	3.920	3.977	3.883

Table 2b Shapiro-Francia test on innovation efficiency.

	Innovation efficiency$_a$ (non-logarithmic)	Innovation efficiency$_a$ (logarithmic)
W’	.276***	.988

** p < .100; ** p < .050; *** p < .010*

Innovation output: to measure innovation output, I look at the total amount of published patents relative to a firm’s sales, in line with earlier studies focused on innovation (Hirshleifer et al., 2012; Zhou et al., 2017). Sales are in thousands of US dollars. One outlier is deleted. After taking the natural logarithm, the distribution resembles a normal distribution.[12] This is further confirmed when using the SF test. On average, innovation output of POEs is higher than innovation output of SOEs (column 4 and 5).

[10] R&D expenditure per patent = $\frac{1}{\text{Median}} \times \$1000 = \frac{1}{0.0193369} \times \$1000 = \$51{,}714.60$
[11] See figure B2 in appendix B for the distribution plot.
[12] See figure B3 in appendix B for the distribution plot.

Table 3a Descriptive statistics of innovation output in 2019.

	Innovation output$_a$ (non-logarithmic)			Innovation output$_a$ (logarithmic)		
	(1)	(2)	(3)	(4)	(5)	(6)
	POE	SOE	All firms	POE	SOE	All firms
Observations	2,133	689	2,822	2,132	352	2,821
Minimum	.000	.000	.000	-17.148	-14.105	-17.148
Maximum	4.817	.792	4.817	-3.868	-6.156	-3.868
Mean	.004	.002	.003	-8.502	-9.099	-8.552
Median	.000	.000	.000	-8.340	-9.118	-8.430
Std. Deviation	.098	.073	.091	2.472	1.823	2.470
Skewness	51.831	2.522	52.669	-.262	.112	-.234
Kurtosis	2701.060	9.243	2789.061	2.548	2.207	2.520

Table 3b Shapiro-Francia test on innovation output.

	Innovation output$_a$ (non-logarithmic)	Innovation output$_a$ (logarithmic)
W'	.515***	.969

** p < .100; ** p < .050; *** p < .010*

Firm value: I copy the method of Hirshleifer et al. (2012) and look at Tobin's Q to proxy firm value. Eighteen outliers are dropped. Afterwards, skewness and kurtosis resemble those associated with a normal distribution.[13] I cannot reject the null hypothesis that my data is normally distributed. Tobin's Q is on average higher for POEs, meaning that these firms are more overvalued by the market and suggesting that investors believe these firms have more growth opportunities.

Table 4a Descriptive statistics of firm value in the period of 2011-2019.

	Firm value$_{a,t}$ (non-logarithmic)			Firm value$_{a,t}$ (logarithmic)		
	(1)	(2)	(3)	(4)	(5)	(6)
	POE	SOE	All firms	POE	SOE	All firms
Observations	11,360	3.264	14,624	11,345	3,261	14,606
Minimum	.004	.014	.004	-3.904	-3.859	-3.904
Maximum	22.686	7.453	22.686	2.887	2.009	2.887
Mean	1.121	.865	1.112	-.274	-.333	-.287
Median	.737	.667	.732	-.304	-.338	-.312
Std. Deviation	1.281	.878	1.277	.863	.974	.876
Skewness	4.445	3.905	4.445	.075	-.268	.010
Kurtosis	22.686	24.235	36.354	3.345	2.805	3.459

[13] See figure B4 in appendix B for the distribution plot.

Table 4b Shapiro-Francia test on firm value.

	Firm value$_a$ (non-logarithmic)	Firm value$_a$ (logarithmic)
W'	.660***	.998

** p < .100; ** p < .050; *** p < .010*

3.2.2 Independent variables

State ownership: In this study I use two different measures for state ownership: (1) a SOE dummy, which takes a one when the company is a SOE and a zero when it is a POE and (2) a continuous state ownership variable which shows the exact percentage of state ownership in a certain company.[14] 22.90 percent of firms in my dataset are SOEs. The average amount of state ownership in a firm is 19.19 percent. For the continuous state ownership variable I find that I can reject the null hypothesis that the variable is normally distributed. Extreme values, such as 0 and 100 percent, are quite common. To limit interpretation problems, I do not use the logarithm of this variable. Instead, I limit the influence of this non-normality by using robust standard errors (Leroy & Rousseeuw, 1987).

Table 5a Descriptive statistics of state ownership in the period of 2011-2019.

	SOE Dummy$_{a,t}$	State ownership$_{a,t}$
Observations	16,095	11,972
Minimum	.000	.000
Maximum	1.000	100.000
Mean	.229	19.186
Median	.000	5.100
Std. Deviation	1.496	5.774
Skewness	6.380	11.212
Kurtosis	41.700	160.425

Table 2b Shapiro-Francia test on state ownership.

	SOE Dummy$_a$	State ownership$_a$
W'	-	.283***

** p < .100; ** p < .050; *** p < .010*

Control variables: several control variables are used in the regressions to prevent omitted variable bias. In line with the tests of Zhou et al. (2017) and Ayyagari et al. (2011), I control for firm size. This is done by including 'revenue' as well as 'total number of employees'

[14] See also under 3. Data for a detailed explanation on how this variable is computed.

(hereafter 'employees') in the regression. The variable 'revenue' is in thousands of US dollars. I also control for firm profitability, by including the 'return on assets using p/l before tax' (ROA). Negative ROA values are dropped, due to problems with interpretation. Lastly, I control for 'firm leverage'. When I regress Tobin's Q on state ownership, I control for firm's growth opportunities by introducing an 'industry PE' variable.[15] After taken the logarithm, for no variable, expect the 'ROA' variable, is the null hypothesis that the data are normally distributed rejected using a 95% confidence interval.

Table 6a Descriptive statistics of control variable in the period of 2011-2019, with the logarithmic value between parentheses. Revenues are in thousands of US dollars.

	$Revenue_{a,t}$	$Employees_{a,t}$	$ROA_{a,t}$	$Leverage_{a,t}$
Observations	16,095	16,095	16,095	16,095
Minimum	242.080	1.000	.001	.028
	(5.489)	(.000)	(-6.908)	(-3.568)
Maximum	472,400,000.000	961,000.000	90.525	351.819
	(19.973)	(13.776)	(4.506)	(5.863)
Mean	4326171.000	11,528.690	8.165	.683
	(12.962)	(7.399)	(1.737)	(-.543)
Median	350958.700	1,380.000	6.527	.625
	(12.768)	(7.230)	(1.876)	(-.470)
Std. Deviation	20,200,000.000	39,074.530	7.019	3.604
	(2.080)	(1.954)	(.980)	(.483)
Skewness	13.243	8.712	2.741	89.981
	(.367)	(.287)	(-1.351)	(-.520)
Kurtosis	232.943	110.914	17.866	8219.002
	(2.802)	(2.759)	(7.504)	(7.895)

Table 6b Shapiro-Francia test on control variables, with the logarithmic value between parentheses.

	$Revenue_{a}$	$Employees_{a}$	ROA_{a}	$Leverage_{a}$
W'	.194***	.293***	.846***	.945**
	(.991)	(.991)	(.895)***	(.965)*

** p < .100; ** p < .050; *** p < .010*

Fixed effects: in my regressions, I absorb industry, country, company and year fixed effects. For panel data analyses, I try out different combinations of these fixed effects to increase the robustness of my results. The 4-digit NACE Rev. 2 classification is used to classify industries.

[15] See par. 4.4 for extensive description of the industry PE variable and table A2 in appendix A for the descriptive statistics.

3.2.3 Correlation

In my dataset, state ownership is negatively correlated with innovation input, efficiency and output, although the correlation is close to zero and insignificant. These results hold for both my SOE dummy and continuous state ownership variable. Furthermore, state ownership is significantly positively correlated with firm size and ROA, while no significant correlation with leverage is observed.

Firms with higher innovation input are positively correlated with innovation output. Interestingly, I do not find a significant positive correlation between innovation efficiency and output. This suggests that firms in my data sample with low innovation efficiency can offset these problems and generate a similar level of innovation output due to higher innovation input.

Table 7 Correlation table.

Variables	1	2	3	4	5	6	7	8	9	10
1. Innovation input$_{a,t}$	-									
2. Innovation efficiency$_{a}$	-.001	-								
3. Innovation output$_{a}$	.320***	.001	-							
4. Tobin's Q$_{a,t}$	.163***	-.001	.037***	-						
5. SOE dummy$_{a,t}$	-.008	-.002	-.004	-.005	-					
6. State ownership$_{a,t}$	-.010	-.001	-.007	.002	.710***	-				
7. Revenue$_{a,t}$	-.012**	-.003	-.006	-.005	.091***	.094***	-			
8. Employees$_{a,t}$	-.020***	-.007	-.008	-.005	.080***	.110***	.581***	-		
9. ROA$_{a,t}$	-.193***	.000	-.077***	.000	.022***	.062***	.030***	.039***	-	
10. Leverage$_{a,t}$	-.003	.001	.000	.118***	.000	-.002	.000	-.001	-.032***	-

$^{*}p < .100$; $^{**}p < .050$; $^{***}p < .010$

3.3 Patent data

There are two points with the patent data that need to be addressed. Firstly, ORBIS only provides patent data of 2019. Therefore, it is not possible to perform a panel data analysis on regressions using patent data. To test whether the data of 2019 are representative for the whole dataset, I run independent t-tests on my variables. I find that no significant difference between the means of 2011-2018 and 2019 of the 'SOE dummy' and 'leverage' variables, meaning that these variables are representative.[16] For the 'continuous state ownership', 'revenue', 'employees' and 'ROA' variables, I do find a significant difference.[17] However, when I

[16] See tables A3a and A7a in appendix A.
[17] See tables A3d, A4a, A5a and A6a in appendix A.

compare the mean of these variables of 2018 with the mean of 2019 this difference disappears.[18] This suggests that these variables are impacted by a time trend. To empirically test this, I regress these variables on a time trend controlling for industry, country and company fixed effects.

$$(3)\quad \text{Dependent variable}_{a,t} = \beta_0 + \beta_1 * \mathrm{Year}_t + \mathrm{Y}_c + \mathrm{Y}_i + \mathrm{Y}_a + \varepsilon$$

β_0 = constant
β_i = regression coefficients
ε = error term

I find that the ‘continuous state ownership’, ‘revenue’ and ‘employees’ variables are affected by a time trend.[19] ROA is not impacted by a time trend.[20] I detrend the variables that are affected by a time trend by taking the residuals and rerun independent t-tests on these residuals. I find that the significant difference in means disappears for the variables ‘state ownership’ and ‘employees’.[21] As such, the 2019 data of these variables are representable for the whole dataset. The 2019 data of the ‘revenue’ and ‘ROA’ variables differentiate significantly from the rest of the dataset. This is not very surprising, returns and revenues tend to fluctuate significantly over time (Schwert, 1989). Since ‘revenues’ and ‘ROA’ are only used as a control variables, the impact of the difference between the means of 2011-2018 and 2019 is limited.

Secondly, ORBIS patent data provides the number of patents and not the value of these patents. As such, the results need to be interpreted cautiously. I solve this limitation by running an additional regression on Tobin’s Q to see if these patents add firm value.

4. State ownership & innovation

4.1 Impact of state ownership on innovation input

In 2015, PricewaterhouseCoopers (PwC) published a report focused on the growing role of SOEs. In this report, the authors, Sturesson et al. (2015), stress the importance of SOEs to deliver societal desirable outcomes. The writers argue for a new framework to assess the performance of SOEs. Too often only financial results are taken into account. Instead, societal capitals, such as innovation, should also be included in a SOE review framework. According to the report it is unclear whether SOEs are correctly incentivized to invest more in innovation. As such, I first give a general picture of the impact of state ownership on innovation input.

[18] See tables A3e, A4b, A5b and A6b in appendix A.
[19] See tables A3f, A4c and A5c in appendix A.
[20] See table A6c in appendix A.
[21] See table A3d and A5a in appendix A.

I run a linear regression over panel data to determine the general impact of state ownership on innovation input. I regress state ownership on innovation input. Furthermore, I add the control variables, a time trend (Y_t) and control for industry (Y_i) fixed effects. To add robustness to my results, I rerun the same regression and add country (Y_c), and company (Y_a) fixed effects.

As such, the following linear regression is run:

$$(4)\ \ \textit{Innovation Input}_{a,t} = \beta_0 + \beta_1 * \textit{SOE Dummy}_{\mathrm{a,t}} + \beta_2 * \textit{Revenue}_{a,t} + \beta_3 * \textit{Employees}_{a,t} + \beta_4 * \mathrm{ROA}_{\mathrm{a,t}} + \beta_5 * \mathrm{Leverage}_{\mathrm{a,t}} + \mathrm{Y_t} + \mathrm{Y_i} + (\mathrm{Y_c} + \mathrm{Y_a}) + \varepsilon$$

β_0 = constant
β_i = regression coefficients
ε = error term

The first regressions, columns 1 and 2 of table 8, show no significant relation between SOEs and innovation input ($p > .05$). It seems that state ownership does not necessarily lead to higher innovation input in SOEs around the world.

The emphasis should be put on the last part of the sentence; converting political connections in additional innovation input might only be possible in corrupt states. Earlier studies on this suggestion provide some evidence. Bertrand, Kramarz, Schoar & Thesmar (2018) using plant-level data from France, a country with low levels of corruption, find that: “there is little evidence that (politically) connected firms benefit from preferential access to government resources, such as subsidies or tax exemptions.” Furthermore, stocks of politically connected firms outperform non-connected firms, but only in highly corrupt countries (Faccio, 2006). This suggests that these firms can only use their political connections in highly corrupt countries.

To find the exact impact of corruption on innovation input, I add a corruption variable. The Corruption Perceptions Index (CPI) is used to compute my proxy for corruption. The index is created by Transparency International and ranks countries based on perceived corruption by experts and business executives in public sectors. The index is a combination of thirteen surveys and several corruption assessments. It is the most used corruption index and as such recommended for research on corruption (Lopes Júnior, Câmara, Rocha & Brasil, 2018; Transparency International, 2020).[22] To test whether innovation input is significantly higher in highly corrupt states, I add a ‘highly corrupt states dummy’ variable to the regression. I define the ten percent most corrupt states according to the CPI as highly corrupt. My highly corrupt states dummy is time-varying.

[22] CPI data before 2012 is not comparable year-over-year and therefore will not be used.

Table 8 Linear regression to test the impact of state ownership on innovation input.

Dependent variable	Innovation Input$_{a,t}$			
	(1)	(2)	(3)	(4)
Explanatory variable	βa (SE)	βa (SE)	βa (SE)	βa (SE)
SOE Dummy$_{a,t}$	-.001 (.011)	.004 (.021)	-.007 (.012)	.005 (.022)
Highly Corrupt State Dummy$_{c,t}$	-	-	-.024 (.025)	-
SOE Dummy$_{a,t}$ × Highly Corrupt State Dummy$_{c,t}$	-	-	.138** (.055)	.051** (.025)
Revenue$_{a,t}$	-.278*** (.020)	-.348*** (.033)	-.271*** (.023)	-.391*** (.038)
Employees$_{a,t}$	.252*** (.020)	.071*** (.023)	.250*** (.023)	.080*** (.024)
ROA$_{a,t}$	.027** (.012)	-.016** (.008)	.023* (.013)	-.013 (.008)
Leverage$_{a,t}$	-.289*** (.031)	-.048* (.029)	-.245*** (.034)	-.037 (.029)
Constant (β_0)	-2.844*** (.771)	-.366 (.387)	-2.899*** (.155)	-.107 (.445)
Country fixed effects	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Company fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Time period	2011-2019	2011-2019	2012-2019	2012-2019
R^2	.471	.932	.475	.936
Number of obs.	16,067	15,739	13,813	13,135

$*p < .100$; $**p < .050$; $***p < .010$

In column 3 and 4, I find that SOEs in corrupt nations can generate significantly more innovation input than POEs in the same nations. The additional innovation input of SOEs in highly corrupt states lies between 5.10% and 13.80%. The results are robust and hold when controlling for different fixed effects. These results provide further evidence to the institutional-based view; it seems that SOEs with government help can acquire more resources needed for innovation. However, this advantage only exists in corrupt nations, where the influence of politicians and business owners is high and financial institutions are relatively underdeveloped. This by no way means that SOEs are better innovators in corrupt nations. However, SOEs in corrupt nations are able to acquire more resources for innovation.

4.2 Impact of state ownership on innovation efficiency

"Politicians in the 20th century have been hypnotised by government . . . in love with it and see no limits to its abilities". But this love affair is coming to an end as the mismanagement and inefficiency of state-owned businesses is becoming more apparent'' – Peter Drucker (1969), former columnist of the Wall Street Journal in his essay 'the sickness of government'.

This supposed inefficiency of SOEs has been well-documented and the main argument for governments to privatize companies. Boardman and Vining (1989) were one of the first researchers to empirically test and confirm the inefficiency of SOEs. Since then, their test has been repeated, extended and improved with newer data, finding similar results. These tests find that SOEs are less productive in the long-run (Ehrlich, Gallais-Hamonno, Liu & Lutter, 1994), have higher costs (Bradshaw, Liao & Ma, 2016), are less efficient in environments of corruption Baum et al. (2019) and as a result have significantly lower firm value (Megginson & Netter, 2001). I test if SOE inefficiency also negatively impacts innovation.

I run a linear regression over cross-sectional data. Innovation efficiency is taken as the dependent variable and the SOE dummy as the main independent variable. Since patent data is only available for 2019, I take the number of pending patents in 2019 as my proxy for patent growth and divide it by the firm's R&D expenditures of 2018 to create my innovation efficiency variable, since on average it takes one year for R&D expenditures to produce a patent (Danguy et al., 2010).

Surprisingly, I find that state ownership in general does not seem to decrease innovation efficiency; no significant relation is found in column 1 of table 9. It could be that SOEs simply put out fewer valuable patents, however I find no evidence for this. More likely is that the benefits of state ownership, more easily being able to become a knowledge network leader, can offset the downsides, the agency problem (Belloc, 2014). This relatively small impact of the agency problem could be explained by the fact that in low corruption environments, political officials are unable to use SOEs for their own personal goals.

In column 2, I indeed find that high corruption levels negatively impact the effect of state ownership on innovation efficiency. In highly corrupt states, innovation efficiency of SOEs is significantly lower than innovation efficiency of POEs. The benefit of being a knowledge network leader is not large enough to overcome the increased agency problem. In the beginning of the year, the IMF (2020) issued a warning on the negative impact corruption has on SOEs and consequently on society. In corrupt nations, political officials are able to use innovation

Table 9 Linear regression to test the impact of state ownership on innovation efficiency.

Dependent variable	Innovation Efficiency$_a$		
	(1)	(2)	(3)
Explanatory variable	βa (SE)	βa (SE)	βa (SE)
SOE Dummy$_a$	-.061 (.039)	-.052 (.039)	-.072* (.041)
SOE Dummy$_a$ × Highly Corrupt State Dummy$_c$	-	-.335*** (.046)	-
SOE Dummy$_a$ × High-tech Sector Dummy$_i$	-	-	.128** (.051)
Revenue$_a$	.125 (.082)	.124 (.082)	.131 (.082)
Employees$_a$	-.157* (.085)	-.155* (.085)	-.163* (.085)
ROA$_a$	-.029 (.049)	-.027 (.050)	-.030 (.050)
Leverage$_a$	.093 (.114)	-.096 (.114)	.093 (.114)
Constant (β_0)	-4.388*** (.541)	-4.388*** (.541)	-4.425*** (.543)
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
R^2	.371	.376	.377
Number of obs.	1,340	1,340	1,340

$*p < .100$; $**p < .050$; $***p < .010$

resources of SOEs for their own personal gain, thereby harming SOE innovation efficiency. This result further confirms the negative effect of corruption on SOE performance.

An area in which SOEs might have higher innovation efficiency, is in high-technology sectors.[23] To test this, I first define what a high-tech sector is. I use the list of high-tech industries from Lee et al. (2016), who based their list on research by the OECD (2011) and provide an updated version.[24] Since the list uses 3-digit SIC codes, I have to convert the industry codes. To my knowledge there is no database converting 3-digit SIC codes to 4-digit NACE Rev. 2 codes. Therefore, I firstly convert the codes to 6-digit NAICS using the NAICS website (NAICS Association, 2020). Secondly, I convert the 6-digit NAICS codes to the 4-digit

[23] See hypothesis 2c for the explanation.
[24] See table A8 in appendix A for the list of innovative sectors.

NACE Rev. 2 codes using the RAMON database of EUROSTAT. My high-tech sector dummy is not time-varying.

In column 3, I find that SOEs in high-tech sectors are able to outperform POEs in high-tech sectors. SOE innovation efficiency is 12.80% higher than their peers. SOEs in high-tech sectors suffer less from the agency problem than other SOEs since monitoring is easier (Zhou et al., 2017) and inefficient firms are significantly more likely to go bankrupt (Ayyagiri et al. 2011). Moreover, SOEs can take more risks than POEs, leading to higher innovation efficiency than their peers (Chen et al., 2008; Belloc, 2014).

4.3 Impact of state ownership on innovation output

In order to increase the robustness of my findings on innovation input and innovation efficiency, I look at innovation output. The total innovation output of a firm depends on how much a firm puts into innovation and how efficient it uses that input. This relation is shown in figure 1. Since I found no significant effect of state ownership on innovation input and innovation efficiency, my test should show that innovation output of SOEs and POEs is not significantly different. It is unclear if this result holds in highly corrupt states; SOEs in highly corrupt states have more access to innovation resources, but are less efficient than POEs. I therefore test which of these two effects dominate. In high-tech sectors, SOEs should generate higher output than POEs. The innovation input of SOEs in high-tech sectors is similar to POEs.[25] However, I found that these SOEs are more efficient than their peers.

To test the effect of state ownership on innovation output, I run a linear regression over cross-sectional data and regress innovation output on my SOE dummy. Since patent data is only available for 2019, I use the total number of published patents of a company in 2019 relative to firm's sales in 2019 as my proxy for innovation output.

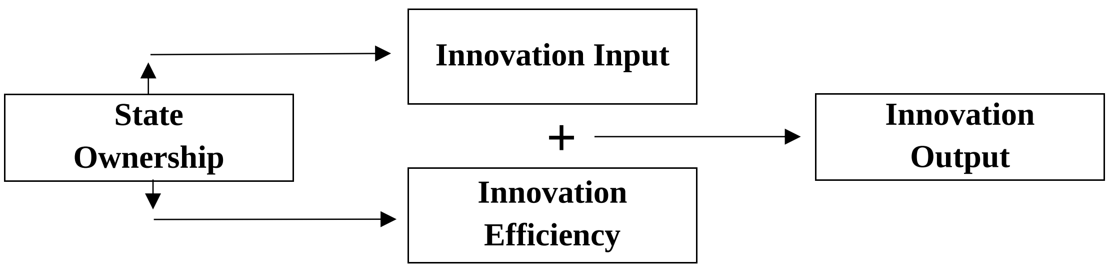

Figure 1 Schematic chart of the impact of state ownership on innovation output and its relation with innovation input and innovation efficiency

[25] See table A9 in appendix A.

Table 10 Linear regression to test the impact of state ownership on innovation output.

Dependent variable	Innovation Output$_a$		
	(1)	(2)	(3)
Explanatory variable	βa (SE)	βa (SE)	βa (SE)
SOE Dummy$_a$	-.003 (.037)	-.002 (.023)	-.013 (.023)
SOE Dummy$_a$ × Highly Corrupt State Dummy$_c$	-	-.006 (.073)	-
SOE Dummy$_a$ × High-tech Sector Dummy$_i$	-	-	.102* (.053)
Revenue$_a$	-.375*** (.058)	-.375*** (.058)	-.375*** (.058)
Employees$_a$	.213*** (.056)	.214*** (.056)	.213*** (.056)
ROA$_a$	-.011 (.037)	-.011 (.037)	-.011 (.037)
Leverage$_a$	-.278*** (.094)	-.278*** (.095)	-.276*** (.094)
Constant (β_0)	-5.305*** (.425)	-5.305*** (.425)	-5.307 (.425)
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
R^2	.552	.552	.553
Number of obs.	2,746	2,746	2,746

$*p < .100$; $**p < .050$; $***p < .010$

In column 1 of table 10 I find no evidence that state ownership in general impacts innovation output. This result was expected since no relation of state ownership with innovation input or efficiency was found. It contradicts earlier findings by Zhou et al. (2017), who found that SOEs in China have significantly higher innovation output. Their results seem to be specific for China. The Chinese Communist Party has made firm innovation government policy (Reuters, 2016; Zhao 2016). As such, political goals and company goals align in the area of firm innovation, which explains the higher SOE innovation output in China.

In column 2, I add corruption to the regression. I find no significant impact. It seems that the higher innovation input and the lower innovation efficiency of SOEs in highly corrupt nations, cancel out each other. In high-tech sectors SOEs are able to outperform their peers (column 3). Their innovation output is 10.20% higher. However, it should be noted that this number is only significant using a 90% statistical significance.

4.4 Firm value

As stated before, ORBIS patent data is limited to the extent that it does not necessarily say something about innovation value and only contains data of 2019. Therefore, I try to find out if this innovation leads to higher firm value using panel data. A regression of firm value on innovation would suffer from endogeneity problems, which would make interpretation difficult. I therefore copy the method of Hirshleifer et al. (2012) and instead investigate a more specific issue, namely if SOEs are able to translate growth opportunities in firm value. To proxy firm value, I use Tobin's Q. For a firm's growth opportunity, I compute the industry price to earnings (PE) ratio. I calculate the average yearly industry PE ratio and take the natural logarithm of that ratio. PE ratios are influenced by both risk (or more specifically the ability to deal with risky opportunities) and the discount rate. The innovation advantage of SOEs could be both the result of a lower discount rate (institutional-based view) and additional risk-taking. Therefore, contrary to the method of the Hirshleifer et al. (2012) paper, I do not subtract the 60-month moving average of the industry PE ratio.[26]

In the first two columns of table 11, I find that my firm's growth measure, the industry PE ratio, positively and significantly predicts Tobin's Q, providing evidence that it indeed captures growth opportunities. The interaction variable 'Industry PE × SOE dummy' in column 3 and 4 shows a significant negative impact on Tobin's Q. SOEs are less able than POEs to convert growth opportunities into actual valuable innovation output, at least in the eyes of shareholders.

Sirmon, Hitt & Ireland (2007), and Wang, Jin and Banister (2019) also found that the effectiveness of resources on innovation capability is negatively impacted by state ownership, but argue that this negative impact is not constant and could vary in different circumstances. In particular the empirical context (i.e highly corrupt countries and high-tech sectors) could impact the results. I find that the interaction variable 'Industry PE × SOE dummy × Highly corrupt state' is negative and significant, controlling for different fixed effects. SOEs in corrupt states are less able to convert growth opportunities in firm value. Only in high-tech sectors, SOE innovation performance significantly improves compared to POEs, suggesting again that SOEs in high-tech sectors are able to overcome the problems of state ownership, such as agency problems. The stand-alone variable of the SOE dummy is significant and positive. However,

[26] The idea behind the Hirshleifer et al. (2012) paper is that overconfident CEOs have an innovation advantage, solely due to additional risk-taking. Therefore, they subtract the 60-month moving average of the PE ratio, guided by the fact that discount rates are more persistent than growth opportunities.

Table 11 Linear regression to test if SOEs can convert growth opportunities in firm value.

Dependent variable	Tobin's $Q_{a,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explanatory variable	βa (SE)	βa (SE)	βa (SE)	βa (SE)	βa (SE)	βa (SE)	βa (SE)	βa (SE)
Industry $PE_{i,t}$	.086*** (.013)	.041*** (.008)	.092*** (.013)	.045*** (.008)	.043** (.022)	.034*** (.008)	.093*** (.013)	.045*** (.008)
SOE $Dummy_{a,t}$	-	-	.042*** (.010)	.012 (.008)	.044*** (.017)	.018** (.009)	.037*** (.010)	.012 (.008)
SOE $Dummy_{a,t}$ × Industry $PE_{i,t}$	-	-	-.026*** (.003)	-.018*** (.006)	-.024*** (.005)	-.013** (.006)	-.024*** (.003)	.017*** (.006)
Highly Corrupt State $Dummy_{c,t}$	-	-	-	-	.207*** (.057)	-	-	-
Highly Corrupt State $Dummy_{c,t}$ × Industry $PE_{i,t}$	-	-	-	-	-.057*** (.016)	-	-	-
SOE $Dummy_{a,t}$ × Highly Corrupt State $Dummy_{c,t}$	-	-	-	-	-.267 (.200)	.154*** (.455)	-	-
SOE $Dummy_{a,t}$ × Highly Corrupt State $Dummy_{c,t}$ × Industry $PE_{i,t}$	-	-	-	-	-.097* (.056)	-.030** (.013)	-	-
SOE $Dummy_{a,t}$ × High-tech Sector $Dummy_{i}$	-	-	-	-	-	-	.195*** (.053)	.012 (.010)
SOE $Dummy_{a,t}$ × High-tech Sector $Dummy_{i}$ × Industry $PE_{i,t}$	-	-	-	-	-	-	.055*** (.015)	.016 (.019)
$Revenue_{a,t}$	.010** (.005)	-.021* (.009)	.010** (.005)	-.022* (.012)	.056** (.010)	-.012 (.011)	.010** (.005)	-.022* (.012)
$Employees_{a,t}$	-.018*** (.005)	-.007 (.009)	-.014*** (.005)	-.007 (.009)	-.047*** (.005)	-.012 (.009)	-.014*** (.005)	-.007 (.009)
$ROA_{a,t}$	-.350*** (.005)	.157*** (.004)	.350*** (.005)	.157*** (.004)	.318*** (.009)	.149*** (.004)	.350*** (.005)	.157*** (.004)
$Leverage_{a,t}$	-.272*** (.001)	-.211*** (.016)	-.275*** (.010)	-.211*** (.016)	-.343*** (.017)	-.190*** (.017)	-.275*** (.010)	-.211*** (.016)
Constant (β_0)	-1.466*** (.061)	-.624*** (.142)	-1.505*** (.061)	-.625*** (.142)	-1.403*** (.105)	-.629*** (.142)	-1.507*** (.061)	-.625*** (.142)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time period	2011-2019		2011-2019		2012-2019		2011-2019	
R^2	.385	.867	.391	.869	.451	.882	.391	.869
Number of obs.	16,067	15,739	16,067	15,739	13,813	13,135	16,067	15,739

$*p < .100$; $**p < .050$; $***p < .010$

due to endogeneity problems, the economic meaning behind this result remains unclear. The same endogeneity problems persist for the interaction variables 'SOE dummy × Highly corrupt state dummy' and 'SOE dummy × High-tech sector dummy'.

4.5 Non-linear effects

Past research on state ownership frequently focused exclusively on wholly and majority owned SOEs. In more recent research, Musacchio et al. (2015) add two more varieties: (1) companies with the state as a minority investor and (2) companies in which the state is strategically involved, but has no or limited financial ownership. While discussing the performance differences between the four types of SOEs, the researchers conclude that theoretically wholly and majority owned SOEs might profit more from government connections in regard to acquiring financial resources, but that this benefit is marginally decreasing as state ownership goes up. On the other hand, wholly and majority owned SOEs suffer significantly from agency problems, while this problem hardly exists for minority and strategically owned SOEs.

I apply this conclusion in an innovation context. According to the institutional-based view, a higher degree of state ownership should be associated with higher innovation input, while the efficiency view argues that state ownership is negatively associated with innovation efficiency. The optimal SOE would have the additional innovation input associated with state ownership, while only limitedly suffering from the agency problem. In this second part of the paper, I look into this non-linear relation between state ownership and innovation, and investigate at which percentage of state ownership innovation is maximized and thus optimal.

4.5.1 Innovation input & efficiency

In the first part of the study, I did not find a significant relation between state ownership and innovation input and efficiency. In the second part, I rerun the same regressions, but use a continuous state ownership variable which has a value between 0 and 100, instead of a SOE dummy. Theory predicts that the impact of state ownership on innovation input increases at a diminishing rate. Agency costs and efficiency problems become increasingly problematic for SOEs at higher levels of state ownership. Therefore, I run the following quadratic regression:

$$(5)\quad \textit{Dependent variable} = \beta_0 + \beta_1 * \textit{State ownership}_{a,t} + \beta_2 * (\textit{State ownership}_{a,t})^2 + \text{Control variables}_{a,t} + \varepsilon$$

β_0 = constant
β_i = regression coefficients
ε = error term

Table 12 Quadratic regression to test the non-linear impact of state ownership on innovation input and efficiency. Variables are time-varying for the regression on innovation input.

Dependent variable	Innovation $\text{Input}_{a,t}$		Innovation Efficiency_{a}
	(1)	(2)	(3)
Explanatory variable	βa (SE)	βa (SE)	βa (SE)
State $\text{Ownership}_{a(,t)}$	.028*** (.007)	.019*** (.007)	.034 (.022)
State $\text{Ownership}_{a(,t)}$ × State $\text{Ownership}_{a(,t)}$	-.000*** (.000)	-.000*** (.000)	-.000* (.000)
$\text{Revenue}_{a(,t)}$	-.026 (.024)	-.237*** (.023)	.171 (.105)
$\text{Employees}_{a(,t)}$	.057** (.024)	.218*** (.023)	-.221** (.126)
$\text{ROA}_{a(,t)}$	.010 (.015)	.016 (.013)	-.028 (.060)
$\text{Leverage}_{a(,t)}$	-.169*** (.035)	-.303*** (.033)	.239* (.136)
Constant (β_0)	-4.589 (.161)	-3.100*** (.158)	-4.519*** (.659)
Country fixed effects	No	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Company fixed effects	No	Yes	No
Time fixed effects	Yes	Yes	No
Time period	2011-2019	2011-2019	2019
R^2	.389	.938	.385
Number of obs.	11,945	11,941	1,011

$^*p < .100$; $^{**}p < .050$; $^{***}p < .010$

I find that state ownership significantly increases innovation input, but that the marginal increase is smaller at higher levels of state ownership. To ensure robustness, I run the regression controlling for different fixed effects in columns 1 and 2. The results remain similar. Even if the government owns only a small amount of the firm, the firm gets enough political connections to overcome most institutional voids. State connections give SOEs access to additional innovation resources, however at high levels of state ownership the impact of an additional percentage of state ownership is limited (Musacchio et al., 2015).

Innovation efficiency exponentially decreases when state ownership increases (column 3). Musacchio et al. (2015) point out that efficiency problems, such as the agency costs, mainly impact SOEs with high levels of state ownership. These conclusions hold when they are applied in an innovation field.

Curiously, figure 2 shows that at high levels of state ownership, innovation input even decreases. To check whether this decrease is statistically significantly, I look at the upbound of the 95% confidence interval.[27] I observe no decrease at high levels of state ownership in the upbound of the 95% confidence interval, meaning that this decrease is not significant.

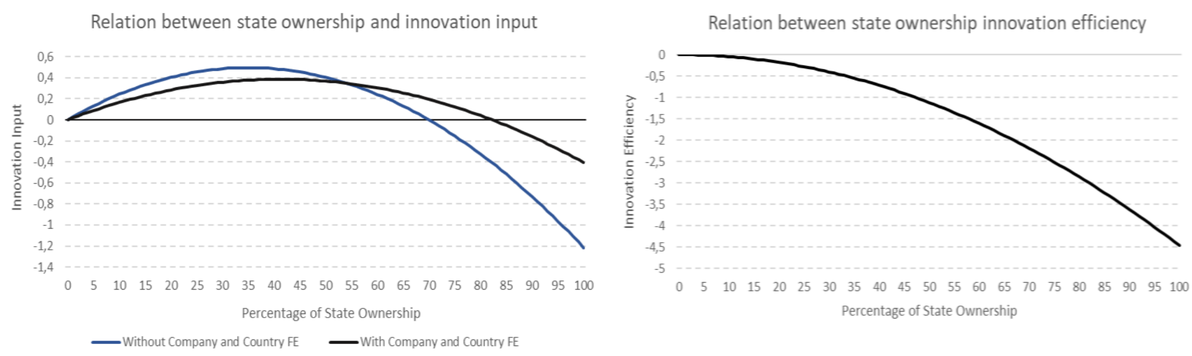

Figure 2 Graphic illustration of the relation between state ownership and innovation input (left) and innovation efficiency (right)

4.5.2 Innovation output

Since the impact of state ownership on innovation input is marginally decreasing and the impact on innovation efficiency exponentially decreasing, innovation output should increase at low levels of state ownership and decrease at high levels of state ownership. Hence, there should exist an inverted U-shaped relation between state ownership and innovation output. To find if this is indeed the case and at which percentage of state ownership innovation is maximized, I run a quadratic regression over cross-section data and regress innovation output on state ownership.

I find that there indeed exists a quadratic relation between state ownership and innovation output in the form of an inverted U-shape when investigating worldwide data (see table 13 and figure 3). I find that innovation output is maximized at 36.77 percent of state ownership.[28] As such, when a firm is owned for less than 36.77 percent by the state, a small increase in state

[27] See figure B5 in appendix B.

[28] Derived after solving: $\frac{d}{dx}$ $0.0253576x - 0.0003448x^2$

Table 13 Quadratic regression to test the non-linear impact of state ownership on innovation output.

Dependent variable	Innovation Output$_a$
	(1)
Explanatory variable	βa (SE)
State Ownership$_a$	.025* (.013)
State Ownership$_a$ × State Ownership$_a$	-.000** (.000)
Revenue$_a$	-.346*** (.069)
Employees$_a$	.204*** (.067)
ROA$_a$	.252 (.044)
Leverage$_a$	.344*** (.111)
Constant (β_0)	-5.637*** (.507)
Country fixed effects	Yes
Industry fixed effects	Yes
R^2	.567
Number of obs.	2,078

$^{*}p < .100$; $^{**}p < .050$; $^{***}p < .010$

ownership would lead to more innovation output. The additional innovation input gained with more state ownership is able to offset the lower innovation efficiency. However, when a firm is owned for more than 36.77 percent by the state, the additional costs of lower efficiency outweigh the benefits of having more innovation input. As such, companies with the state as a minority investor seem to be the best innovators. The 36.77 percent somewhat differentiates from the 29.12 percent Zhou et al. (2017) found. This difference might be explained by the fact that at certain levels of ownership stockholders gain additional monitoring rights, which limit the agency costs. The exact level of ownership at which these additional rights are gained, differentiates between countries. And contrary to the paper of Zhou et al., this paper does not only investigate SOEs in China, but uses a worldwide data sample.

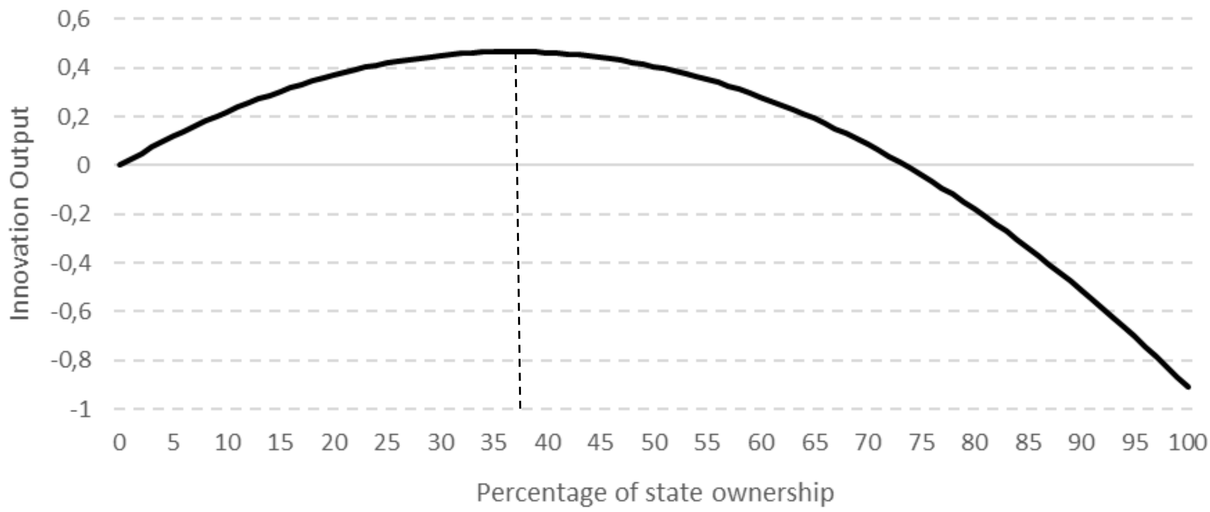

Figure 3 Graphic illustration of the relation between state ownership and innovation output

4.5.3 Firm value

To ensure that my results on innovation output are not simply driven by the number of patents, but by actual valuable innovation output, I run a quadratic regression on Tobin's Q, my proxy for firm value. To limit endogeneity problems, I again add the 'Industry PE' variable as a proxy for a firm's growth opportunity.

In both column 1 and 2 of table 14 my interaction variables 'State ownership × Industry PE' and 'State ownership × State ownership × Industry PE' are nonsignificant, making interpretation difficult. As such, I do not find significant evidence that a company which is for 36.77 percent owned by a state, has the optimal capabilities of turning growth opportunities into valuable innovation output. It seems that these SOEs are able to increase the number of patents, but that, at least from a shareholder's point of view, these innovations add no significant additional value.

Interestingly, when using a SOE dummy instead of a continuous state ownership variable, I found a significant negative relation between state ownership and the ability to convert growth opportunities in firm value. This difference might be explained by the fact that in the first part of my study, my SOE dummy only included firms which were ultimately owned or de facto controlled by public sector entities. This suggests that minority owned SOEs, which were not included in the SOE dummy, suffer less from problems in converting growth opportunities in firm value than majority and wholly owned SOEs, which were included in the SOE dummy.

Table 14 Quadratic regression to test at which percentage of state ownership the conversion of growth opportunities in firm value is maximized.

Dependent variable	Tobin's $Q_{a,t}$	
	(1)	(2)
Explanatory variable	βa	βa
	(SE)	(SE)
Industry $PE_{i,t}$	$.094^{***}$	$.043^{***}$
	(.016)	(.009)
State $Ownership_{a,t}$	$-.110^{*}$	-.013
	(.057)	(.032)
State $Ownership_{a,t}$ × State $Ownership_{a,t}$	$-.001^{***}$	.000
	(.000)	(.000)
State $Ownership_{a,t}$ × Industry $PE_{i,t}$	-.036	.009
	(.032)	(.018)
State $Ownership_{a,t}$ × State $Ownership_{a,t}$ × Industry $PE_{i,t}$	.005	-.001
	(.005)	(.002)
$Revenue_{a,t}$	-.004	$-.042^{***}$
	(.006)	(.013)
$Employees_{a,t}$	$-.017^{***}$	-.005
	(.005)	(.010)
$ROA_{a,t}$	$-.344^{***}$	$.147^{***}$
	(.006)	(.005)
$Leverage_{a,t}$	$-.257^{***}$	$-.184^{***}$
	(.011)	(.019)
Constant (β_0)	-1.352^{***}	$-.339^{***}$
	(.074)	(.169)
Country fixed effects	No	Yes
Industry fixed effects	Yes	Yes
Company fixed effects	No	Yes
Year fixed effects	Yes	Yes
Time trend	2011-2019	
R^2	.394	.882
Number of obs.	11,945	11,941

$*p < .100$; $**p < .050$; $***p < .010$

5. Conclusion

In this paper, I have researched the impact of state ownership on innovation. I structured the hypotheses in such a way that they help answer the research question. In the first part of my study, I used a SOE dummy. I did not find any significant evidence that SOEs have higher innovation input than POEs. In the second part of my study, I used a continuous state ownership variable. I found that state ownership positively impacts innovation input, but that this increase is marginally decreasing. This provides strong evidence that the relation between state ownership and innovation input is non-linear. Furthermore, it seems that the results highly depend on the empirical context. When I specifically look at SOEs in countries with high levels of corruption, which suffer from significant institutional voids, I find significant evidence that state ownership can increase innovation input. In corrupt states, political connections help SOEs acquire more resources for innovation.

The relation between state ownership and innovation efficiency is also non-linear and highly circumstantial. When using the SOE dummy, I found that SOEs in general do not have lower innovation efficiency than POEs. However, when using a continuous state ownership variable, I did find a significant negative relation between state ownership and innovation efficiency. The impact becomes exponentially worse at higher levels of state ownership. Furthermore, in environments with high corruption levels, SOEs suffer from additional innovation agency and efficiency problems. In those environments it is easier for political officials to misuse SOEs for their own personal gains. In high-tech sectors, SOEs seem to be able to overcome these agency problems. Moreover, due to their superior risk-taking abilities, SOEs in high-tech sectors have significantly higher innovation efficiency than POEs.

To increase the robustness of these findings, I looked at innovation output. Innovation output is the result of both input and efficiency. Since SOEs do not have significantly higher innovation input or efficiency than POEs, there should be no significant difference in innovation output. In line with this prediction, I found no significant difference between patent output of SOEs and patent output of POEs. The SOE patents are however, at least according to the shareholders, less valuable than the POE patents, leading to lower firm value for SOEs. Also in highly corrupt states SOEs do not have significant higher innovation output. The higher innovation input and lower efficiency of SOEs in highly corrupt nations, cancel each other out. SOEs in corrupt nations suffer from lower firm value at a given level of growth opportunities, suggesting that their patents are less valuable than the patents of POEs. Only SOEs in high-tech sectors are able to generate a higher innovation output than their peers due to their high innovation efficiency. This higher innovation output leads to higher firm value.

When looking at the non-linear relation between state ownership and innovation output, I found an inverted U-shaped. SOEs which are for 36.77 percent owned by the state, generate the highest innovation output. I found no evidence that this higher innovation output leads to higher firm value, making interpretation difficult. However, my results do show that SOEs do not necessarily underperform in converting growth opportunities into firm value. At least minority owned SOEs seem to perform similar to POEs.

In conclusion, the impact of state ownership is highly circumstantial and non-linear. In general, SOEs do not seem to be better innovators. However, in some empirical contexts, such as in high-tech sectors, they can outperform POEs. Furthermore, I found that there exists an inverted U-shaped relation between state ownership and innovation output with 36.77 percent as the optimal share of state ownership. Therefore, companies with the state as a minority owner seem to outperform their peers. The exact optimal percentage of state ownership varies between nations. A significant factor influencing the optimal percentage of SOE state ownership seems to be the corporate law code of a country, which dictates at which ownership percentage shareholders get additional rights.

While in recent years there has been some research focused on state ownership and innovation by Ayyagiri et al. (2011), Belloc (2014), Zhou et al. (2017) and Wang et al. (2019), my research shows the relation between state ownership and innovation on a global scale and in varying empirical contexts, and thereby adds to the growing literature on state ownership. In times when the importance of state ownership is growing and more people are calling for socially responsible SOEs, my paper can help states decide in which cases privatization is desirable, and to a lesser extent at which percentage.

5.1 Suggestions for further research

Further research could focus on the main shortcoming of this paper, the absence of time-varying and precise patent data. Considering that the patent database of ORBIS is new, it is expected that in the future time-varying data will be available, allowing for more precise testing of the relation between state ownership and innovation (ORBIS, 2020). Furthermore, patents of a firm are not necessarily the result of its R&D program. A company can simply buy patents from another firm. Therefore, more precise data could improve the predictive power of my tests.

Secondly, the earlier discussed PwC report argued that there should be a new framework for evaluating SOE performance; societal capitals should be on the forefront of this evaluation. Societal capitals not discussed in this paper, such as welfare and environmental capitals, would be interesting topics to research and can further add to the main goal of this paper, researching in which cases privatization is desirable. While some limited literature on these topics exists, they are largely neglected, making them interesting to look into.

Considering that my research topic was partly inspired by the research suggestions of Inoue et al. (2013), I end my paper with similar words as they did. If I have learned one thing during my study, it is that financial economics is about so much more than just money; financial decisions have considerable societal implications. Therefore, I sincerely hope that my work can help spark future research on the societal impact of state capitalism.

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Appendix A

Table A1 List of SOEs per country.

Country	Frequency	Country	Frequency
Austria	35	Laos	9
Bangladesh	9	Lithuania	27
Belgium	26	Malaysia	98
Brazil	88	Mongolia	9
Cambodia	9	Norway	27
China	300	Pakistan	36
Czech Republic	9	Poland	87
Denmark	9	Portugal	9
Finland	36	Romania	18
France	45	Russia	409
Germany	36	Singapore	62
Greece	26	Slovenia	27
Hong Kong (China)	9	Sri Lanka	9
Hungary	9	Sweden	18
Indonesia	159	Switzerland	18
Italy	36	Taiwan	27
Kazakhstan	26	Thailand	45
Korea, South	27	United Kingdom	9
Total	1,838		

Table 2a Descriptive statistics of Industry PE in the period of 2011-2019.

	Industry $PE_{i,t}$
Observations	16,095
Minimum	.867 (-.143)
Maximum	287.115 (5.660)
Mean	40.616 (3.634)
Median	39.532 (3.677)
Std. Deviation	15.847 (.381)
Skewness	2.099 (-.416)
Kurtosis	18.083 (4.802)

Table 2b Shapiro-Francia test on Industry PE.

	Industry PE_t
W'	$.892^{***}$ $(.980)^{*}$

* $p < .100$; ** $p < .050$; *** $p < .010$

Table A3a Independent t-test to measure the difference between state ownership in 2011-2018, and revenue in 2019. State ownership is defined with a dummy. Equal variances are assumed. The mean of the SOE dummy in 2019 does not significantly differ from the mean of the SOE dummy in 2011-2018. The variable is not detrended from year fixed effects, since I find no significant year fixed effects (see table A3c). The t-value the result of the t-test and df the number of degrees of freedom.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	12,997	.176	.012		
2019	1,340	.212	.038		
T-test				-.974	14,407

Table A3b Independent t-test to measure the difference between state ownership in 2018, and state ownership in 2019. State ownership is defined with a dummy. Equal variances are assumed. The means of the SOE dummies in 2018 and 2019 do not significantly differ. The variable is not detrended from year fixed effects, since I find no significant year fixed effects (see table A3c). The t-value the result of the t-test and df the number of degrees of freedom.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,496	.207	.037		
2019	1,340	.212	.038		
T-test				-.011	2,906

Table A3c Linear regression to test whether state ownership (dummy) is impacted by a time trend.

Dependent variable	State Ownership$_{a,t}$
	(1)
Explanatory variable	βa (SE)
Year$_t$	.000 (.000)
Constant (β_0)	-.001 (1.121)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.986
Number of obs.	14,230

Table A3d Independent t-test to measure the difference between state ownership in 2011-2018, and state ownership in 2019. State ownership is defined with a continuous variable. Equal variances are assumed. The mean state ownership of 2019 is significantly higher than the mean state ownership in 2011-2018. After detrending the variable from year fixed effects, the means no longer significantly differentiate from each other using a 95% confidence interval. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	9,644	19.568 (17.942)	.559		
2019	1,097	24.412 (20.520)	2.350		
T-test				-2.639*** (-1.404)*	10,739

Table A3e Independent t-test to measure the difference between state ownership in 2018, and state ownership in 2019. State ownership is defined with a continuous variable. Equal variances are assumed. The mean state ownership of 2018 and 2019 do not significantly differ. After detrending the variable from year fixed effects, the difference stays nonsignificant. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,137	22.123 (18.720)	1.978		
2019	1,097	24.412 (20.520)	2.350		
T-test				-.747 (-.588)	2,232

Table A3f Linear regression to test whether state ownership (continuous variable) is impacted by a time trend.

Dependent variable	State Ownership$_{a,t}$
	(1)
Explanatory variable	βa (SE)
Year$_t$	.487*** (.018)
Constant (β_0)	-96.160*** (24.626)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.846
Number of obs.	10,392

$* p < .100$; $** p < .050$; $*** p < .010$

Table A4a Independent t-test to measure the difference between revenue in 2011-2018, and revenue in 2019. Equal variances are assumed. The mean revenue of 2019 is significantly higher than the mean revenue in 2011-2018. After detrending the variable from year fixed effects, the means still significantly differentiate. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	12,997	13.080 (13.019)	.018		
2019	1,340	13.316 (13.166)	.055		
T-test				-4.069*** (-2.545)***	14,407

Table A4b Independent t-test to measure the difference between revenue in 2018, and revenue in 2019. Equal variances are assumed. The mean revenue of 2018 and 2019 do not significantly differ. After detrending the variable from year fixed effects, the difference stays nonsignificant. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,496	13.335 (13.204)	.054		
2019	1,340	13.316 (13.166)	.055		
T-test				.251 (.495)	2,906

Table A4c Linear regression to test whether revenue is impacted by a time trend.

Dependent variable	Revenue$_{a,t}$
	(1)
Explanatory variable	βa (SE)
Year$_t$	.019*** (.001)
Constant (β_0)	-24.460*** (1.989)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.990
Number of obs.	14,230

$*p < .100$; $**p < .050$; $***p < .010$

Table A5a Independent t-test to measure the difference between employees in 2011-2018, an employees in 2019. Equal variances are assumed. The mean number of employees of 2019 is significantly higher than the mean number of employees of 2011-2018. After detrending the variable from year fixed effects, the significant difference disappears. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	12,997	7.506 (7.411)	.017		
2019	1,340	7.685 (7.451)	.052		
T-test				-3.270*** (-.733)	14,407

Table A5b Independent t-test to measure the difference between employees in 2018, and employees in 2019. Equal variances are assumed. The mean number of employees of 2019 does not significantly differentiate from the mean number of employees in 2018. After detrending the variable from year fixed effects, the difference stays nonsignificant. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,496	7.695 (7.491)	.051		
2019	1,340	7.685 (7.451)	.051		
T-test				.139 (.540)	2,906

Table A5c Linear regression to test whether employees is impacted by a time trend.

Dependent variable	$Employees_{a,t}$
	(1)
Explanatory variable	βa (SE)
$Year_t$	.029*** (.001)
Constant (β_0)	-51.268*** (2.270)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.981
Number of obs.	14,230

$* p < .100$; $** p < .050$; $*** p < .010$

Table A6a Independent t-test to measure the difference between ROA in 2011-2018, and ROA in 2019. Equal variances are assumed. The mean ROA of 2019 is significantly lower than the mean ROA in 2011-2018. The variable is not detrended from year fixed effects, since I find no significant year fixed effects (see table A6c). The t-value the result of the t-test and df the number of degrees of freedom.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	12,997	1.745	.008		
2019	1,340	1.656	.026		
T-test				3.328***	14,407

Table A6b Independent t-test to measure the difference between ROA in 2018, and ROA in 2019. Equal variances are assumed. The mean ROA of 2019 is significantly lower than the mean ROA in 2018. The variable is not detrended from year fixed effects, since I find no significant year fixed effects (see table A6c). The t-value the result of the t-test and df the number of degrees of freedom.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,496	1.819	.023		
2019	1,340	1.656	.026		
T-test				4.702***	2,906

Table A6c Linear regression to test whether ROA is impacted by a time trend.

Dependent variable	$ROA_{a,t}$
	(1)
Explanatory variable	βa (SE)
$Year_t$	.002*** (.003)
Constant (β_0)	-1.284*** (5.070)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.585
Number of obs.	14,230

** $p < .100$; ** $p < .050$; *** $p < .010$*

Table A7a Independent t-test to measure the difference between leverage in 2011-2018 and leverage in 2019. Equal variances are assumed. The mean leverage of 2011-2018 and 2019 do not significantly differ. After detrending the variable from year fixed effects, the difference becomes significant. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2011-2018	12,997	-.534 (-.502)	.004		
2019	1,340	-.546 (-.468)	.013		
T-test				.909 (-2.528)***	14,407

Table A7b Independent t-test to measure the difference between leverage in 2018, and leverage in 2019. Equal variances are assumed. The mean leverage of 2018 and 2019 do not significantly differ. After detrending the variable from year fixed effects, the difference stays nonsignificant. The t-value is the result of the t-test, df the number of degrees of freedom and the de-trended value is between parentheses.

Group	Obs.	Mean	Std. Error	T-value	Df
2018	1,496	-.549 (-.479)	.012		
2019	1,340	-.546 (-.468)	.013		
T-test				-.049 (-.588)	2,906

Table A7c Linear regression to test whether leverage is impacted by a time trend.

Dependent variable	$Leverage_{a,t}$
	(1)
Explanatory variable	βa (SE)
$Year_t$	-.010***
	(.001)
Constant (β_0)	18.971***
	(1.426)
Country fixed effects	Yes
Industry fixed effects	Yes
Company fixed effects	Yes
R^2	.887
Number of obs.	14,230

** $p < .100$; ** $p < .050$; *** $p < .010$*

Table A8 List of high-technology industries.

SIC CODE	**Industry**
281	Industrial inorganic chemicals
282	Plastics materials and synthetic resins, synthetic
283	Drugs
284	Soap, detergents, and cleaning preparations
285	Paints, varnishes, lacquers, enamels, and allied
286	Industrial organic chemicals
287	Agricultural chemicals
289	Miscellaneous chemical products
351	Engines and turbines
356	General industrial machinery and equipment
357	Computer and office equipment
361	Electric transmission and distribution equipment
366	Communications equipment
371	Motor vehicles and motor vehicle equipment
372	Aircraft and parts
382	Laboratory apparatus and analytical, optical, measuring, and controlling instruments
384	Surgical, medical, and dental instruments and supplies
386	Photographic equipment and supplies
737	Computer programming, data processing, and other computer related services
871	Engineering, architectural, and surveying services
873	Research, development, and testing services

Source: Lee et al. (2016) and OECD (2011)

Table A9 Linear regression to test the impact of SOEs in high-tech sectors on innovation input.

Dependent variable	Innovation Input$_{a,t}$	
	(1)	(2)
Explanatory variable	βa (SE)	βa (SE)
SOE Dummy$_{a,t}$	.000 (.012)	.043 (.021)
SOE Dummy$_{a,t}$ × High-tech sector Dummy$_i$	.002 (.034)	.000 (.033)
Revenue$_{a,t}$	-.277*** (.020)	-.348 (.034)
Employees$_{a,t}$	.252*** (.021)	.071*** (.023)
ROA$_{a,t}$	.027** (.012)	-.016*** (.008)
Leverage$_{a,t}$	-.289*** (.027)	-.048* (.029)
Constant (β_0)	-2.844*** (.140)	-.375 (.387)
Country fixed effects	No	Yes
Industry fixed effects	Yes	Yes
Company fixed effects	No	Yes
Year fixed effects	Yes	Yes
Time period	2011-2019	2011-2019
R^2	.471	.936
Number of obs.	16,067	15,739

$^*p < .100$; $^{**}p < .050$; $^{***}p < .010$

Appendix B

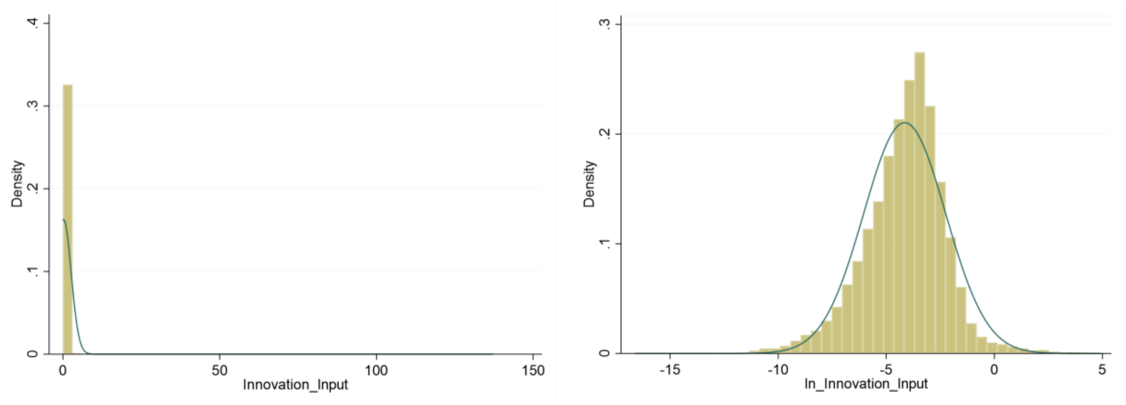

Figure B1 Distribution of Innovation input before (left) and after (right) limiting kurtosis and skewness

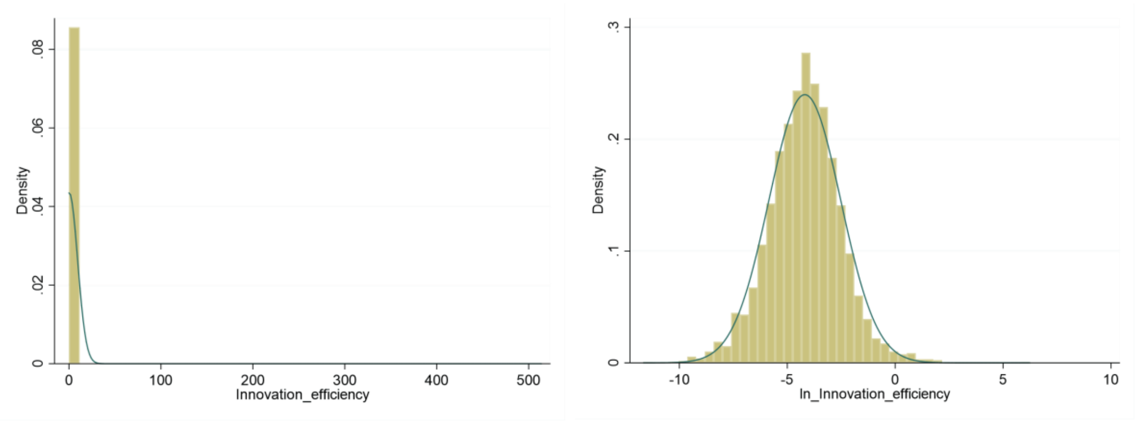

Figure B2 Distribution of published patents before (left) and after (right) limiting kurtosis and skewness

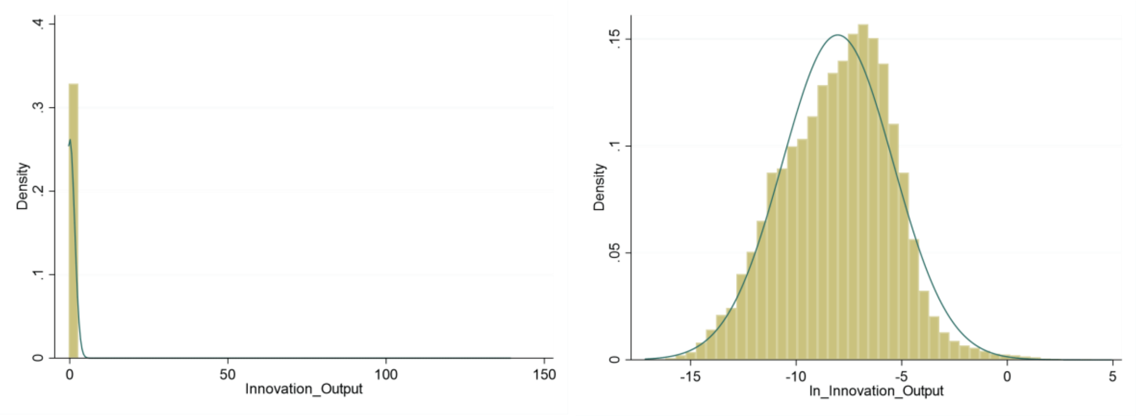

Figure B3 Distribution of patent growth in 2019 before (left) and after (right) limiting kurtosis and skewness

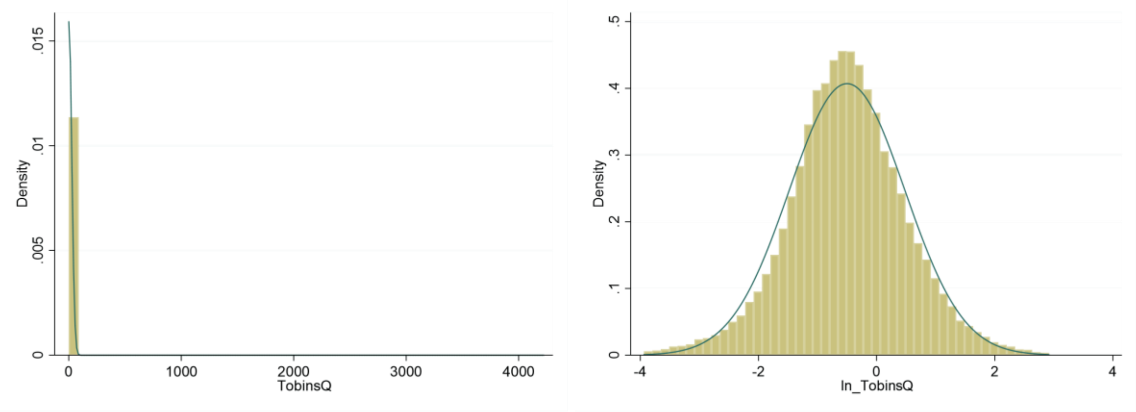

Figure B4 Distribution of Tobin's Q in 2019 before (left) and after (right) limiting kurtosis and skewness

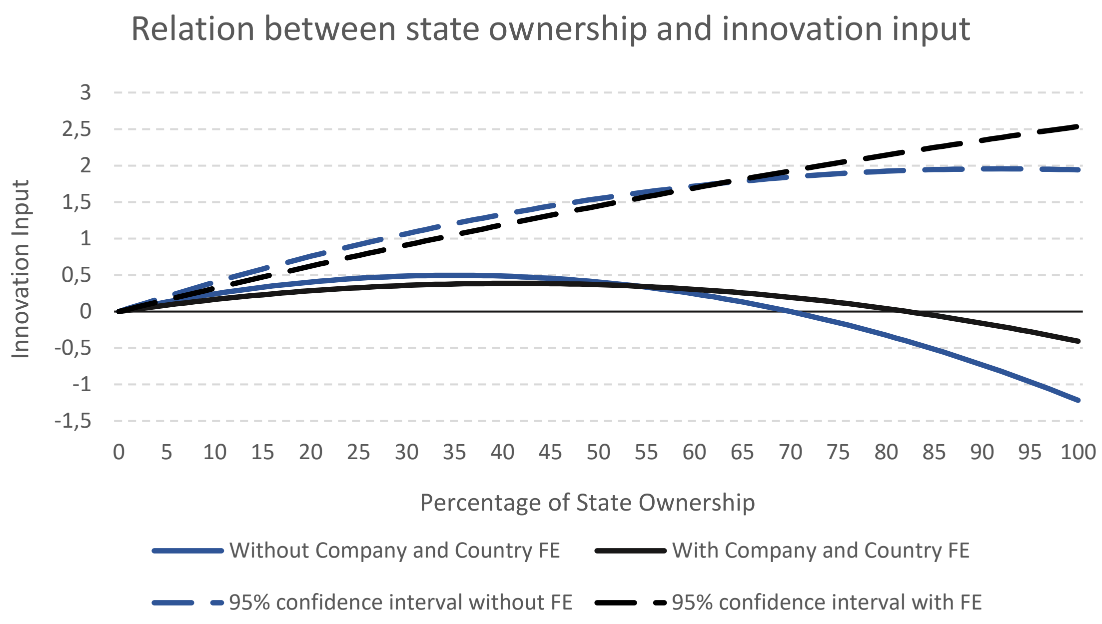

Figure B5 Graphic illustration of the relation between state ownership and innovation input with the upbound of the 95% confidence interval