International Review of Financial Analysis 96 (2024) 103619

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Firms' organisation capital: Do peers matter?

Joye Khoo [a], Adrian (Wai Kong) Cheung [b,*]

[a] School of Accounting, Economics and Finance, Curtin University, Australia
[b] Faculty of Finance, City University of Macau, Macao, China

ARTICLE INFO

JEL classification:
G23
G32

Keywords:
Organisation capital
Peer effect
Mimicking
Industry effect

ABSTRACT

This paper explores the role of industry-level factor in determining organisation capital. Using US dataset, we show evidence that peers' organisation capital matters, and firms mimic their peers in formulating organisation capital. We also find that mimicking behaviour is more pronounced for firms operating in competitive product markets and environments with more information asymmetry, as is consistent with theoretical explanations for why firms imitate each other. Our results are robust to alternative measures of organisation capital and endogeneity concerns.

1. Introduction

The literature recognises the crucial role of intangible assets in amplifying firms' productivity and efficiency (i.e., Peters & Taylor, 2017). A large share of intangible assets is contributed by organisation capital (Corrado, Hulten, & Sichel, 2009), which is defined as the accumulated stock of knowledge and capabilities embodied in firms' key talent that generates increased operational efficiency and superior performance (Eisfeldt & Papanikolaou, 2013; Lev & Radhakrishnan, 2005; Lev, Radhakrishnan, & Zhang, 2009). The literature document supportive evidence on the contributing role of organisation capital in shaping firm-level outcomes, including higher productivity (Atkeson & Kehoe, 2005), lower cost of equity (Attig & Cleary, 2014), and resource-sustainable competitive advantage (Hasan & Cheung, 2018). Furthermore, organisation capital is a critical source of competitive advantage that is difficult to imitate (Lev & Radhakrishnan, 2005) and a key driver of corporate value, growth, and innovation (i.e., Francis, Mani, Sharma, & Wu, 2021). Considering the outstanding features of organisation capital and the property of organisation capital being difficult to imitate, we examine whether a US firm's adoption of organisation capital depends on its industry peers, i.e. how other firms' organisation capital affects that of the focal firm. In this study, we attempt to address this question by examining whether and how peer firms influence a firm's organisation capital decisions.

Existing literature show evidence supporting the beneficial side of organisation capital that plays in firms' productivity (Atkeson & Kehoe, 2005) and performance (Attig & Cleary, 2014). For instance, firms with more organisation capital face stable operation and better performance which, in turn, are likely to reduce future cash flow uncertainty as well as improve the long-term competition. In addition, organisation capital captures firm-specific elements, such as the unique business processes firms have developed and the key talents of employees with difficult-to-replicate characteristics. These distinctive characteristics have strong bonds with firms' future growth, such as innovation (Francis et al., 2021). However, some studies highlight the detrimental side of organisation capital. Eisfeldt and Papanikolaou (2013) highlight that organisation capital is a firm-specific production factor that is embedded in a firm's superior talents, who typically have outside options and can move across firms. Losing talents is a key risk of firms investing in organisation capital. It is because key talents tend to take their valuable organisation capital contribution and expertise with them to another firm. Therefore, firms with more organisation capital are exposed to the loss of key talents as well as the threat of losing business secrets to their competitors, which further increases the volatility of firms' future cash flow stemming from such losses. Similarly, Hasan and Cheung (2023) find that organisation capital is positively related to both idiosyncratic risk and total risk. Khoo and Cheung (2023) suggest that firms encounter hidden cost of organisation capital by showing evidence of the use of trade credit decreases with firms' organisation capital.

Do firms compete with their peers by investing in organisation capital? Answering this question enhances our understanding of the determinants of organisation capital. Most studies implicitly assume that

* Corresponding author at: Faculty of Finance, City University of Macau, Taipa, Macao, China.
E-mail addresses: s.khoo@cbs.curtin.edu.au (J. Khoo), adriancheung@cityu.edu.mo (A.(W.K. Cheung).

https://doi.org/10.1016/j.irfa.2024.103619
Received 27 July 2023; Received in revised form 15 September 2024; Accepted 21 September 2024
Available online 24 September 2024
1057-5219/

firms manage organisation capital in isolation, and independently of the actions and characteristics of their rival peers (see e.g., Eisfeldt & Papanikolaou, 2013; Hasan & Cheung, 2018). As such, the question of whether a firm's investment in organisation capital is affected by its peers remains unexplored. This study aims to fill this gap. This is an important gap in the literature, as a substantial body of research shows evidence that mimicking peers plays a central role in shaping corporate decisions. Two mechanisms of imitation are well documented by Lieberman and Asaba (2006): they are rivalry-based imitation and information-based imitation. First, some studies show supportive evidence that mimicking behaviour arises from a learning and reputational motive (Foucault & Fresard, 2014; Francis, Hasan, & Kostova, 2016; Gyimah, Machokoto, & Sikochi, 2020; Leary & Roberts, 2014), whereby firms replicate the policies of industry peers, as they perceive their rivals to possess superior information. For instance, Foucault and Fresard (2014) document that firms' investments are related positively to their peers' valuations, and that such relationships arise because peers' valuations convey information to managers about their growth opportunities. Gyimah et al. (2020) find that firms increase their accounts receivable in response to an increase in the accounts receivable of their industry peers, in order to signal information about their quality or to establish a reputation. Second, as postulated by Lieberman and Asaba (2006), fierce competitive pressure in the product market leads to mimicking behaviour which, in turn, enables firms to deal with rivals' aggressive actions while maintaining their market power. Adhikari and Agrawal (2018) find peer influence on dividends, and Asad, Boubaker, and Dang (2021) show peer influence on trade credit provision. These mimicking behaviours are mainly driven by product market competition.

Using a sample of 32,626 firm-year observations over the period 1997 to 2017, we partition organisation capital into components attributable to different sources of variation (industry, firm and other variations) and show evidence that industry-level variation is an important component that determines the variation of firms' organisation capital. In particular, 37 % of the variation in organisation capital is due to firm variation while 26 % of the variation is due to industry variation. This evidence is consistent with the findings of Atkeson and Kehoe (2005) and Corrado et al. (2009) that the aggregate size of organisation capital at industry level is substantial and important in an economy.

To explore further the role of industry-level factor in determining organisation capital, we examine whether and how peer effect affects organisation capital and find that firms' organisation capital is associated positively with that of their peers. As it is well-documented that endogeneity arises in the attempt to infer whether the average group behaviour influences the behaviour of an individual firm that belongs to the group (Leary & Roberts, 2014; Manski, 1993), we employ two instrumental variable techniques. First, following prior studies (Hasan, Lobo, & Qiu, 2021; Li, Qiu, & Shen, 2018), we use state-level unemployment insurance benefits as an instrumental variable in two-stage least-squares (2*sls*) regression. Higher unemployment insurance reduces worker changes of jobs, implying that firms located in states with high unemployment insurance are likely to invest more in organisation capital. Second, we follow Lewbel (2012) approach and employ a heteroskedasticity-based instrument. The estimated results from 2*sls* analyses indicate that peer firms have a significant effect on organisation capital, suggesting that our evidence of peer effect on organisation capital is not driven by endogeneity problems.

Next, we examine the effects of product market competition on the peer effect of organisation capital by partitioning our sample into subgroups based on market competition, allowing us to test directly the predictions of the rivalry-based theory of imitation, as postulated by Lieberman and Asaba (2006). This theory argues that competition is related to the decision of whether or not to imitate peers, and several studies provide supportive findings. Gyimah et al. (2020) show that firms mimic their peers in formulating trade credit policies in highly competitive product markets. Adhikari and Agrawal (2018) find that firms imitate peers' payout policies to maintain their competitive parity. Earlier studies highlight the importance of organisation capital in nurturing firm performance, productivity and innovation (Eisfeldt & Papanikolaou, 2013; Francis et al., 2021) by conferring a competitive edge over peers and, in turn, building up the ability to bargain and compete in the product market. Consistent with Lieberman and Asaba (2006) and Adhikari and Agrawal (2018), we find evidence that mimicking behaviour is more pronounced for firms in more competitive industries, revealing that firms mimic the organisation capital of their peers to maintain (or enhance) their competitive positioning or to limit rivalry in the industry.

Furthermore, we also explore the effects of the information environment on the peer effect of organisation capital by partitioning our sample into subgroups based on information asymmetry, thus, allowing us to analyse the predictions of the information-based theory of imitation, as documented by Lieberman and Asaba (2006). Information-based theory argues that firms are likely to take actions and mimic their peers based on information implicit in the actions of other firms. Gyimah et al. (2020) show that the peer effect of trade credit are more prevalent for firms operating in high asymmetric information environments. Consistent with Gyimah et al. (2020) and Lieberman and Asaba (2006), we find evidence that peer influence on organisation capital is more pronounced for firms that operate in environments with more information asymmetry, implying that firms mimic the organisation capital of their peers to enhance their reputation or to signal their quality to outsiders.

This paper contributes to the existing literature in several ways. First, unlike prior studies that explore organisation capital at industry-level or macro-level (i.e., Atkeson & Kehoe, 2005; Corrado et al., 2009), or a pioneering work by Lev and Radhakrishnan (2005) and subsequent studies that examine organisation capital at firm-level (i.e., Hasan et al., 2021; Hasan & Cheung, 2023; Sun, Li, & Ghosal, 2020), this paper considers how an industry-level factor (i.e., peer effect) affects organisation capital at firm-level. We build on and add to the literature on organisation capital, revealing that mimicking behaviour plays an important role in shaping firms' organisation capital. Different from Hasan and Cheung (2018)'s claim that organisation capital is difficult to mimic and replicate, this paper shows evidence that there is a peer mimicking effect in organisation capital. We find that a one standard deviation increase in peer organisation capital is associated with an increase in firms' organisation capital by 14.36 %. In addition, our findings also suggest that the peer effect of organisation capital resembles a contagion process, which explains why the level of organisation capital appears to cluster within industries. The market is likely to prioritise firms with more organisation capital when their competitors possess lower levels of organisation capital. If competitors invest more in organisation capital, it is beneficial for the firm to behave the same. Second, we contribute to the growing literature that examine the influence of peer firms on corporate decisions, including trade credit policies (Asad et al., 2021; Gyimah et al., 2020), capital structure (Leary & Roberts, 2014) and dividend policies (Grennan, 2019). Third, to the best of our knowledge, this study is the first to investigate the influence of peer firms on organisation capital in a comprehensive sample covering different industries, and show that the evidence of Chen and Inklaar (2016) that the spill-over effects of organisation capital are weak is confined to manufacturing sector only and cannot be generalized to other industries. Fourth, to shed light on some key factors that influence organisation capital, we document and show evidence that the motives for mimicking reported in the literature, help explain variations in organisation capital. In line with the rivalry-based theory that imitation increases in competitive markets (Lieberman & Asaba, 2006), we show evidence that firms imitate the organisation capital of their peers to enhance their competitive positioning in their industries. Furthermore, consistent with the information-based theory that imitation heightens in more information asymmetry environments (Lieberman & Asaba, 2006), we also provide evidence that peer influence on organisation capital firms operates to enhance their reputations or signal their quality to outsiders. Taken together, our findings reveal that investing in organisation capital is a channel though which firms can achieve improvements in their level of competitiveness (information asymmetry) in the product market (information environment) against rivals.

Chen and Inklaar (2016) (henceforth Chen and Inklaar (2016)) examine the spill over effects of organisation capital. Based on a sample of 1266 US manufacturing firms over the period 1982–2011, they find no significant spill over effects and only limited evidence for market-stealing effects on the market value of firms. Our paper is different in the following ways. First, consistent with Goodridge, Haskel, and Wallis (2017) and Corrado, Haskel, and Jona-Lasinio (2017), who find evidence of positive productivity spillovers of non-R&D intangible assets based on industry-level and economy-wide data, we also find a positive peer effect at firm-level data. Our sample covers not only manufacturing firms but also firms of other industries (except financial and utilities firms). This can account for the difference between Chen and Inklaar (2016) and our paper.[1] Another possible reason is that Chen and Inklaar (2016) defines peer firms in terms of technology proximity (i.e., number of patents), which is largely an output-based measure and ignores the process-based measure. Note that organisation capital is exactly a concept designed to capture innovations in process, which is particularly more important in non-manufacturing firms, such as services-based firms. Our measure of peer firms is based on product similarity developed by Hoberg and Phillips (2016), which is presumably more comprehensive than technology proximity. Second, Chen and Inklaar (2016) is concerned with productivity spill over, i.e., how organisation capital affects output (i.e., firm productivity), while our paper is concerned with peer effect of organisation capital, i.e., how organisation capital of peer firms affects that of the firm. As such, their approach is indirect as it is concerned with the consequence of spill over. Our approach is more direct as it shows whether the organisation capital between the firm and its peers are correlated.

The rest of this paper proceeds as follows. Section 2 provides details of the data and variables used. Section 3 presents the research method employed in this paper. Empirical results and conclusions are discussed in Sections 4 and 5, respectively.

2. Hypothesis development

To test whether and how firms mimic their peers' organisation capital, we develop our hypothesis based on rivalry-based motive for mimicking proposed by Lieberman and Asaba (2006), which suggests that firms mimic their peers to maintain competitive parity or limit rivalry. That is, firms would undertake strategic actions, such as introduction of alike products and the adoption of akin organizational forms, to mitigate competitive pressure or maintain their relative competitive advantage over peers. For instance, as industry competition heightens, focal firms appear to mimic the innovation of their peers in order to keep ahead or abreast of rivals (Machokoto, Gyimah, & Ntim, 2021). As a result, mimicking rivals' actions can neutralize threats to focal firms' competitive position (Lieberman & Asaba, 2006; Ross & Sharapov, 2015).

In the context of organisation capital, Lev and Radhakrishnan (2005) show that organisation capital leads to increased operational efficiency and superior performance and, along this view, firms may mimic their peers' organisation capital to stay competitive. For example, it is well known that Walmart possesses supply chain management system that smoothens their inventory management system. Walmart competitor, such as Amazon, also provides an end-to-end, fully automated set of supply chain services that provide sellers with a complete solution to move products quickly and reliably from manufacturing locations to customers around the globe. Taken together, we posit that firms are more inclined to mimic the organisation capital of their industry peers to maintain the competitive parity or to limit rivalry in their industry. Thus, we derive our main hypothesis as follows:

Hypothesis 1. firms imitate the organisation capital of their industry peers.

Next, we examine the conjecture that, when product market competition is high, firms are more likely to be active in responding to the organisation capital of their peers. According to the rivalry-based theory (Lieberman & Asaba, 2006), imitation increases in competitive markets to maintain competitive parity. On the one hand, high organisation capital enables firms to achieve efficient production and stable business operations that, in turn, result in positive firm-level outcomes, such as increased productivity (Atkeson & Kehoe, 2005), better operating stock performance (Lev et al., 2009) and more cash holdings (Marwick, Hasan, & Luo, 2020). These highlight the importance of organisation capital in managing product market competition, particularly in highly competitive circumstances. That is, a focal firm has a stronger incentive to imitate peer firms' organisation capital in order to maintain competitive parity or to limit rivalry. On the other hand, in a less competitive environment, the incentive to imitate is expected to be lower, because there is less need to imitate peer firms' organisation capital in order to signal quality. Taken together, consistent with the rivalry-based theory, mimicking the organisation capital of peer firms is expected to be more pronounced in more competitive industries. This leads to our second hypothesis:

Hypothesis 2. the peer effect is stronger for firms operating in more competitive market.

It is well documented that organisation capital enables the firm to achieve efficient production and a stable business operation, leading to higher productivity (Atkeson & Kehoe, 2005), better firm performance (Lev et al., 2009), and cash accumulation that avoids costly external financing (Marwick et al., 2020). Stable operation and better performance, are likely to reduce the uncertainty of future cash flows and improve the long-term sustainability of firms with high levels of organisation capital. However, organisation capital is related to more complex information than typical physical assets or financial resources. The possession of highly complex information related to organisation capital, is likely to induce information asymmetry between firms and outside investors. For instance, Kim, Park, and Song (2021) show evidence that analysts' forecasts tend be more biased and less accurate when they cover firms with high levels of organisation capital.

In the literature on peer effects, the information-based theory suggest that, in environments with high information asymmetry, firms are incentivised to mimic their peers for reputation enhancement or to signal their quality to outsiders (Adhikari & Agrawal, 2018; Lieberman & Asaba, 2006). Incorporating the beneficial perspective of organisation capital and its complexities, we argue that the focal firm has a stronger incentive to imitate peer firms' organisation capital in order to signal their quality to investors. Our third hypothesis is shown as follows:

Hypothesis 3. the peer effect is stronger for firms operating in more information asymmetry.

3. Data and key variables

3.1. Selection of industry peers

Following recent papers that explore the peer effect, such as Asad et al. (2021), Cao, Fang, and Lei (2021) and Foucault and Fresard

[1] We also check if our results would be similar to that of C&I (2016) when our sample is confined to manufacturing firms only. The (untabulated) result shows that the mimicking behaviour of peer firms has no significant impact on the firm's organisation capital and firm value, suggesting that C&I (2016) results may be applicable to manufacturing industry only and cannot be generalized to other industries.

(2014), we form pairs of peer firms using the text-based Network Industry Classifications (TNIC) system of Hoberg and Phillips (2016). Using Hoberg and Phillips (2016)'s text-based analysis of product descriptions in 10-K filings for any given pair of firms in a year, firms' peers are defined based on the similarity between firms' product descriptions listed in their annual 10-K filings filed every year with the Securities and Exchange Commission (SEC). In each year, Hoberg and Phillips (2016) compute a measure of product similarity for every pair of firms through parsing their product descriptions. In other words, firms identify peers as their competitors depending on the similarity or differences in their products, which is the key of classifying industries. The measurement is based on the relative number of words that both firms commonly used in their product description. As the number of common words both firms use in describing their products increase, the higher the similarity score between the firms. That is, firms *i* and *j* use more of the same words and are likely to be membership pairs. Hoberg and Phillips (2016) define each firm *i*'s industry to include all firms *j* with pairwise similarities relative to *i* above a pre-specified minimum similarity threshold. The threshold is pre-specified to maintain the same proportion of possible membership pairs as three-digit Standard Industrial Classification (SIC) codes. Given our focus on peer mimicking, the pairwise TNIC system is shown to be more informative and more suitable than other industry classification systems, such as the SIC system and the North American Industry Classification System (NAICS), which evolved slowly in response to product market developments and rarely reclassify firms over time (Cao et al., 2021). For example, when a firm impose adjustment on its product range or decide to enter a new product market, the set of industry peers changes accordingly. As industry peers are defined relative to each firm, thus each firm has its own distinct set of industry peers, which varies over time depending on changes in technologies and product descriptions. This provides a richer definition of product similarity.

3.2. Measure of organisation capital and control variables

Ample studies document that substantial portions of selling, general and administrative (*sga*) expenditures are invested into items that generate firms' organisation capital, including labour costs, such as wages, employee incentives, marketing expenses, recruiting and consulting costs, employee training costs and investments in information and distribution systems (Eisfeldt & Papanikolaou, 2013; Lev et al., 2009; Lev & Radhakrishnan, 2005). Peters and Taylor (2017) argue that expenditures on employee training strengthen human capital, and advertising expenses enhance brand reputation, both of which are captured by *sga* expenditure. This implies that any value gained through these expenditures is firm-specific, and attributable to firms' key talent, which generates, in turn, heightened firm organisation capital.

Eisfeldt and Papanikolaou (2013) measure organisation capital as the accumulation of a fraction of past *sga* expenditure using the perpetual inventory method as below:

$$OC_{i,t} = (1-\delta_{0C})OC_{i,t-1} + \frac{sga_{i,t}}{cpi_t}$$

where $sga_{i,t}$ denotes firm *i*'s selling, general and administrative expenditure at time *t*. δ_0 denotes the depreciation rate of organisation capital, cpi_t denotes the consumer price index, and $OC_{i,t}$ denotes firm-specific organisation capital at time *t*. The initial stock of organisation capital for each firm is computed as follows:

$$OC_{i,t0} = \frac{sga_{i,t} \times \theta_0}{g+\delta_0}$$

where θ_0 represents the percentage of *sga* expenditure invested into organisation capital and *g* represents the growth in the flow of organisation capital, estimated as the average growth of firm-level *sga* expenditure. Following Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017), we assume 30 % of *sga* spending as an investment into organisation capital. The initial stock of organisation capital for each firm is computed based on the growth rate of 10 % and the depreciation rate for organisation capital is to be assumed to be 15 %, following Francis et al. (2021) and Kim et al. (2021).[2] Lastly, the stock of organisation capital is scaled by firms' total assets, denoted as *oc_ep_ta*, which is widely used in the literature (Francis et al., 2021; Gao, Leung, & Qiu, 2021; Kim et al., 2021). *oc_ep_ta* is the proxy for organisation capital used in the baseline regression.

In addition, we also employ the organisation capital measure of Peters and Taylor (2017) as an alternative measure, because this measure is also widely used in prior studies (Francis et al., 2021; Hasan & Cheung, 2018). Similar to Eisfeldt and Papanikolaou (2013), Peters and Taylor (2017) measure firms' stock of organisation capital by capitalising *sga* expenditures using the perpetual inventory method as follows:

$$OC_{i,t} = (1-\delta_0)OC_{i,t-1} + sga_{i,t} \times \theta_0$$

Most variables are discussed earlier. Following Peters and Taylor (2017), we assume a 20 % depreciation rate for organisation capital. As a robustness check, we use Peters and Taylor (2017)'s measure of organisation capital scaled by total assets, denoted as *oc_ta*.

Data are collected from Compustat and Centre for Research in Security Prices (CRSP) databases through Wharton Research Data Services (WRDS) for the period 1996–2017. We start sampling from 1996, because data on Hoberg and Phillips (2016)'s TNIC is available from 1996. Firms operating in the financial sector (SIC codes 6000–6999), and firms in the utility sector (SIC codes 4900–4999) are excluded from the sample. Following Peters and Taylor (2017), firms with less than $5 million in physical capital are excluded, to eliminate the potential bias resulting from smaller firms. Furthermore, observations with missing variables for the baseline regression model are excluded. All variables are winsorized at their 1st and 99th percentiles to minimise the potential impact of outliers. The final sample consists of 10,321 unique firms with 32,626 firm-year observations.

Table 1 presents the sample distribution by industry using the Fama and French (1997) 48-sector classifications. The sample covers 44 industries, and the industries that are most represented in the sample are business services (15.72 %), retail (8.17 %), and electronic equipment (7.49 %). When analysing the sample distribution by number of firms, we observe a similar pattern. The most representative industries are business services (1086 unique firms), electronic equipment (418 unique firms) and retail (373 unique firms). Other industries account for less than 7 % of the firm-year observations, suggesting a wide distribution within our sample. Overall, the distribution of our final sample across industries is consistent with Chen, Liu, Ma, and Martin (2017) and Jory, Khieu, Ngo, and Phan (2020).

4. Empirical model

4.1. Baseline estimation model

A well-known challenge in estimating peer effect derives from the reflection problem, and describes a specific form of endogeneity, as documented by Manski (1993). This problem refers to a situation where

[2] Organisation capital measure is assumed to be 30 % of *sga* spending. Peters and Taylor (2017) show that the estimated θ_0 is 0.38 in the consumer industry, 0.51 in the high-tech industry, and 0.24 in the health care industry, which are all in the neighborhood of the assumed 0.3 value. Following Eisfeldt and Papanikolaou (2013), we assume the growth rate for investment in organisation capital to be 10 %, which is the average growth rate of *sga* expenditures in real terms for firms in Compustat database. Similarly, following Eisfeldt and Papanikolaou (2013), we assume a 15 % depreciation rate for organisation capital, which is the rate used by Bureau of Economic Analysis for the estimation of R&D capital stock.

Table 1
Sample distribution.

Industry	Observation	Percent	# of firms
1 Agriculture	85	0.26	20
2 Food Products	673	2.06	110
3 Candy & Soda	141	0.43	17
4 Beer & Liquor	142	0.44	21
5 Tobacco Products	33	0.10	7
6 Recreation	180	0.55	46
7 Entertainment	580	1.78	102
8 Printing and Publishing	168	0.51	37
9 Consumer Goods	441	1.35	86
10 Apparel	642	1.97	90
11 Healthcare	736	2.26	124
12 Medical Equipment	1503	4.61	242
13 Pharmaceutical Products	1466	4.49	264
14 Chemicals	791	2.42	122
15 Rubber and Plastic Products	209	0.64	55
16 Textiles	83	0.25	31
17 Construction Materials	700	2.15	125
18 Construction	403	1.24	72
19 Steel Works	403	1.24	86
20 Fabricated Products	92	0.28	24
21 Machinery	1182	3.62	203
22 Electrical Equipment	495	1.52	79
23 Automobiles and Trucks	536	1.64	93
24 Aircraft	208	0.64	24
25 Shipbuilding, Railroad Equipment	98	0.30	17
26 Defence	75	0.23	10
27 Precious Metals	64	0.20	15
28 Non-Metallic and Industrial Metal Mining	151	0.46	27
29 Coal	103	0.32	20
30 Petroleum and Natural Gas	2026	6.21	367
32 Communication	1319	4.04	266
33 Personal Services	511	1.57	90
34 Business Services	5128	15.72	1086
35 Computers	1400	4.29	288
36 Electronic Equipment	2443	7.49	418
37 Measuring and Control Equipment	836	2.56	130
38 Business Supplies	321	0.98	61
39 Shipping Containers	123	0.38	18
40 Transportation	830	2.54	144
41 Wholesale	1329	4.07	234
42 Retail	2667	8.17	373
43 Restaurants, Hotels, Motels	989	3.03	168
Others	321	0.98	78
Total	32,626	100	5890

a correlation between a firm's organisation capital and the policies of its industry peers does not confirm that peer effect exists, because firms may adopt similar organisation capital simultaneously in response to common industry shocks. For example, changes in investment opportunities or tax incentives may lead all firms within an industry to adjust their organisation capital simultaneously. Thus, it can be difficult to disentangle the peer effect on organisation capital from common industry effects, when industry characteristics play a role in dictating the organisation capital of individual firms.

Following Leary and Roberts (2014), Foucault and Fresard (2014), Asad et al. (2021) and Grennan (2019), we use the following model to investigate the mimicking behaviour on firms' organisation capital:

$$y_{ijt} = \alpha_0 + \alpha_1 \overline{y}_{-ijt} + \alpha_2 \overline{X}_{-ijt-1} + \alpha_3 X_{ijt-1} + \mu_i + \vartheta_t + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} refers to the organisation capital for firm *i* in industry *j* at time *t* (proxied by *oc_ep_ta*), α_0 is a constant, and $\overline{y}_{-ijt}$ is peer firms' organisation capital, excluding firm *i* (proxied by *p_oc_ep_ta*). $\overline{X}_{-ijt-1}$ and X_{-ijt-1} show the peer firms' average and firm-specific characteristics, respectively, that are found to be associated with organisation capital in the literature (e.g., Eisfeldt and Papanikolaou (2013)). In Eq. (1), $\overline{X}_{-ijt-1}$ and X_{-ijt-1} are adopted to address the possibility that firms adopt a similar organisation capital simultaneously in response to common industry shocks. The peer firms' average characteristics are calculated as the average of all firms within an industry-year, excluding the observations for firm *i*. μ_i and ϑ_t indicate the firm and year specific effects, respectively, while $\varepsilon_{i,t}$ signifies the idiosyncratic error term.

All the control variables are defined in the Appendix. Following Blanco-Mazagatos, de Quevedo-Puente, and Delgado-García (2018), we control for *fsize* (natural logarithm of total assets) and *roa* (operating income before depreciation scaled by total assets) because several studies show evidence that larger firms and more profitable firms are better able to attract, assimilate, and retain key talents with high skills (Anh Do & Bui, 2022; Lin, Lin, Song, & Li, 2011). We also control for *age* (natural logarithm of the difference between the first year the firm appears in CRSP and the current year), given that firms appear to recruit more key talents human capital as they age (Pennings, Lee, & Van Witteloostuijn, 1998). Regier and Rouen (2023) find that firms with high growth opportunity tend to possess more future value of personnel expenses, which is positively associated with characteristics of human-capital intensive firms. Along this view, we control for *mb* (market value of assets scaled by total assets). Considering that the construction of financial measure for the economic value of organisation capital is highly associated with firms' expenditure on input resource - selling, general and administrative expenses (*sga*), Venieris, Naoum, and Vlismas (2015) show evidence on the association of *sga* with firms' revenue growth. We are therefore control for *sg* (natural logarithm of difference between the current and the prior level of sales scaled by the prior level of sales).

4.2. Instrumental variable for 2sls estimation

Endogeneity may take other forms in our setting. For examples, the regression of an individual firm's organisation capital on its peer averages could be a spurious one because of the endogenous selection of firms into peer groups (Leary & Roberts, 2014). Furthermore, there could be common omitted factors that affect both firms and their peers' organisation capital, leading to omitted variable bias (Leary & Roberts, 2014).

To alleviate these endogeneity concerns, we use two estimation techniques. First, following prior studies (Hasan et al., 2021; Li, Li, Wang, & Zhang, 2018), we use state-level unemployment insurance benefits as an instrumental variable in a *2sls* regression.[3] Higher unemployment insurance benefits are likely to reduce job switches and employee turnover risk, thus, firms located in states with greater unemployment insurance benefits are likely to invest more in organisation capital (Li, Li, et al., 2018) via accumulating industry- and firm-specific human capital, which satisfies the relevance condition. As unemployment insurance benefits are likely to take some time to come to fruition, we follow Gao et al. (2021), and use p_ui_{t-1} (peer firms' average unemployment insurance benefits lagged by one year) to account for the possibility that unemployment insurance benefits may have a lagged effect on organisation capital. Data are collected from the U.S. Department of Labor's Database on Significant Provisions of State Unemployment Insurance Laws. Following Hasan et al. (2021), unemployment insurance benefit generosity is measured by summation of the natural logarithm of the product of the maximum benefit amount and the maximum duration allowed, and we merge the state-year unemployment insurance measure with our firm-year panel, based on the firm's

[3] To address the endogeneity concerns, ample studies use the equity idiosyncratic return shock as an instrumental variable in the 2sls estimation (e.g., Asad et al., 2021; Gyimah et al., 2020; Leary & Roberts, 2014). However, using the idiosyncratic stock returns computed by the Fama and French (1993) three-factor model or the Carhart (1997) model as instrumental variable, the results do not pass the standard instrumental variable test, and show that the instrumental variable of idiosyncratic stock returns is a weak instrument in our setting. This suggests that idiosyncratic risk is not a good instrumental variable in our setting.

historical headquarters' state.

Second, we follow Lewbel (2012) and employ an instrumental variable approach with heteroskedasticity-based instruments. Lewbel (2012) develops a new method that can address the endogeneity concern in the absence of traditional identifying information, such as external instruments, or when no other such information is available. This method exploits model heteroscedasticity to construct instruments using the available regressors, and identification can be achieved by having regressors that are uncorrelated with the product of heteroskedastic errors, which is a feature of many models where error correlations are due to an unobserved common factor. Assume a sample of observations of endogenous variables, Y_1 and Y_2, and a vector of control variables, X.

$$Y_1 = X'\sigma + Y_2\beta + \varepsilon_1$$

$$Y_2 = X'\rho + \varepsilon_2$$

where the errors, ε_1 and ε_2, may be correlated. Assuming there is no element of X that can be used as an instrument for Y_2, Lewbel (2012)'s approach provides generated instruments that can be constructed through exploiting information contained in the heteroscedasticity of ε_2. Let Z be some or all of the elements of X. σ and ρ can be obtained through estimating an ordinary linear two stage least squares regression of Y_1 on X and Y_2, using X and $(Z - \overline{Z})\widehat{\varepsilon_2}$ as instruments, where $\overline{Z}$ is the sample mean of Z. Tests of heteroskedasticity, over-identification and weak instruments can be performed to check the quality of the generated instruments. Several recent studies employ Lewbel (2012)'s technique (e.g., Fortin & Ragued, 2017; Millimet & Roy, 2016), and show evidence that Lewbel (2012)'s generated instruments perform well.[4]

5. Empirical results

5.1. Summary statistics

We report the summary statistics of the key variables in Table 2. Similar to Francis et al. (2021) and Marwick et al. (2020), the averages of organisation capital measures are 0.7416 (*oc_ep_ta*) and 0.2874 (*oc_ta*); with standard deviations of 0.6984 and 0.2631, respectively. In addition, the averaged organisation capitals of the peer firms are 0.9331 (*p_oc_ep_ta*) and 0.2887 (*p_oc_ta*), which are close to the mean of the sample firms.

5.2. Firm and industry component of organisation capital

We start off with decomposing organisation capital into firm, industry and year components, and check the contribution of these levels to the variation in the firm-level measures of organisation capital. To this end, we use the analysis of variance (ANOVA) which decomposes the variance of organisation capital into three components. They are industry variance, firm variance and error variance. The estimates are reported in Table 3. In Table 3, we observe that the variance component at the industry and firm levels are 0.1285, and 0.1824, respectively. Given the total variance is 0.4894, these components contribute to the total variance approximately 26.26 % (industry) and 37.27 % (firm).[5] This suggests that more than one-quarter of the variation in organisation capital is due to industry variations. The result highlights the importance of the industry-level component in determining firms' organisation capital.

Table 2
Summary statistics.

Variable	Mean	Median	S.D.	25 %	75 %
oc_ep_ta	0.7416	0.546	0.6984	0.2694	0.9736
oc_ta	0.2874	0.2093	0.2631	0.1033	0.3849
roa_{t-1}	0.1160	0.1268	0.1327	0.0744	0.1830
$fsize_{t-1}$	6.2472	6.1456	1.7886	4.9418	7.4557
mb_{t-1}	2.2040	1.6696	1.6071	1.2243	2.5480
age_{t-1}	2.1641	2.1972	0.6186	1.7918	2.6391
sg_{t-1}	4.0073	4.0411	1.8996	2.7611	5.2627
p_oc_ep_ta	0.9331	0.8208	0.8007	0.4545	1.1787
p_oc_ta	0.2887	0.2473	0.1873	0.151	0.3747
p_roa_{t-1}	0.0730	0.1022	0.1073	0.0369	0.1424
p_fsize_{t-1}	6.2485	6.1724	1.0579	5.4618	6.9787
p_mb_{t-1}	2.2067	1.9293	1.0536	1.5385	2.5688
p_age_{t-1}	2.1773	2.1972	0.3955	1.8900	2.4456
p_sg_{t-1}	4.0795	4.0463	1.0503	3.3689	4.7126

This table reports the summary statistics of the key variables used in this study. oc_*ep_ta* is the organisation capital estimated by Peters and Taylor (2017) scaled by total assets. *p_oc_ep_ta* is the average organisation capital following Eisfeldt and Papanikolaou (2013) of TNIC-based peers, excluding firm *i*. Firm size (*fsize*) is measured by natural logarithm of total assets. Market-to-book ratio (*mb*) is measured by market value of assets divide by total assets. Profitability (*roa*) is measured by operating income before depreciation divide by total assets. Sales growth (*sg*) is measured by natural logarithm of difference between the current and the prior level of sales, scaled by the prior level of sales. Firm age (*age*) is measured by natural log of the difference between the first year the firm appears in CRSP and the current year. *p_fsize* is the average firm size of TNIC-based peers, excluding firm *i*. *p_mb* is the average market-to-book ratio of TNIC-based peers, excluding firm *i*. *p_roa* is the average profitability of TNIC-based peers, excluding firm *i*. *p_sg* is the average sales growth of TNIC-based peers, excluding firm *i*. *p_age* is average firm age of TNIC-based peers, excluding firm *i*. The definitions of the variables used in this table are also presented in the Appendix. * indicates significance at the 10 % level. ** indicates significance at the 5 % level. *** indicates significance at the 1 % level.

Table 3
Analysis of variance.

Analysis of variance	
	oc_ep_ta
Industry component:	0.1285
Firm component:	0.1824
Error component:	0.1785

This table presents the estimated results obtained from the analysis of variance (ANOVA) which decomposes the variance of organisation capital into three components: industry variance, firm variance and error variance. As documented by Eisfeldt and Papanikolaou (2013), organisation capital is defined as the accumulated stock of knowledge and capabilities embodied in firms' key talent.

5.3. Mimicking behaviour on firms' organisation capital

5.3.1. Fixed effects regression

To investigate whether peer firms' organisation capital influences a focal firm's organisation capital beyond the factors documented in the literature, we estimate Eq. (1) using panel fixed effects approach. The dependent variable is the focal firm's organisation capital (*oc_ep_ta*) and the key interest independent variable is the peer firms' organisation capital (*p_oc_ep_ta*). If mimicking behaviour exists, we expect the coefficient on *p_oc_ep_ta* to be positive and significant. First, we report the estimated results obtained from fixed effects regression (when year- and firm-fixed effects are controlled for) in Column (1) of Table 4. The coefficient on *p_oc_ep_ta* (0.0251) is positive and statistically significant at

[4] To this end, we use a STATA command called "*ivreg2h*" and generate the set of instruments.

[5] Rather than analysing industry variance based on SIC, we also conduct ANOVA using Fama and French (1997) 48-sector classification. Using the Fama and French (1997) 48-sector classification, we find that industry component contributes to the total variance approximately 20.5 % (30 %) when *oc_ep_ta* (*oc_ta*) is used while the contribution of firm component is 44 % (45.7 %). Similar to Table 3, the results highlight that at least one quintile of the variation in organisation capital is due to industry variations.

Table 4
The effect of peer firms on organisation capital.

		Second-stage regression from 2*sls*	
	Fixed effects regression	Instrumental variable regression	Lewbel (2012) approach
Variable:	*oc_ep_ta* (1)	*oc_ep_ta* (2)	*oc_ep_ta* (3)
p_oc_ep_ta	0.0251***	0.1794*	0.0365**
	0.005	*0.092*	*0.016*
roa_{t-1}	−0.6221***	−0.5974***	−0.6201***
	0.056	*0.058*	*0.057*
$fsize_{t-1}$	−0.2532***	−0.2520***	−0.2531***
	0.010	*0.010*	*0.010*
mb_{t-1}	−0.0328***	−0.0317***	−0.0328***
	0.003	*0.003*	*0.003*
age_{t-1}	0.2381***	0.2573***	0.2395***
	0.018	*0.022*	*0.019*
sg_{t-1}	−0.0119***	−0.0124***	−0.0119***
	0.002	*0.002*	*0.002*
p_roa_{t-1}	0.0351	0.3817*	0.0607
	0.053	*0.213*	*0.065*
p_fsize_{t-1}	0.0150***	0.0203***	0.0154***
	0.006	*0.006*	*0.006*
p_mb_{t-1}	−0.0210***	−0.0187***	−0.0208***
	0.004	*0.005*	*0.004*
p_age_{t-1}	−0.0991***	−0.0916***	−0.0986***
	0.017	*0.018*	*0.017*
p_sg_{t-1}	−0.0006	−0.0018	−0.0007
	0.003	*0.003*	*0.003*
Year effects	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Observations	32,626	32,626	32,626
Under-identification test (Chi^2 p-value)		0.0000	0.0000
Weak identification test (Cragg-Donald Wald F statistic)		64.164	1299.004
Over-identification test (Chi^2 *p*-value)		Not applicable	0.5321

This table presents the estimation results of Eq. (1), which relates organisation capital to firm-specific and peer firms' average characteristics. *oc_ep_ta* is the organisation capital estimated by Peters and Taylor (2017) scaled by total assets. *p_oc_ep_ta* is the average organisation capital following Eisfeldt and Papanikolaou (2013) of TNIC-based peers, excluding firm *i*. Firm size (*fsize*) is measured by natural logarithm of total assets. Market-to-book ratio (*mb*) is measured by market value of assets divide by total assets. Profitability (*roa*) is measured by operating income before depreciation divide by total assets. Sales growth (*sg*) is measured by natural logarithm of difference between the current and the prior level of sales, scaled by the prior level of sales. Firm age (*age*) is measured by natural log of the difference between the first year the firm appears in CRSP and the current year. *p_fsize* is the average firm size of TNIC-based peers, excluding firm *i*. *p_mb* is the average market-to-book ratio of TNIC-based peers, excluding firm *i*. *p_roa* is the average profitability of TNIC-based peers, excluding firm *i*. *p_sg* is the average sales growth of TNIC-based peers, excluding firm *i*. *p_age* is average firm age of TNIC-based peers, excluding firm *i*. Robust standard errors (in *italic*) are clustered at the firm level. The definitions of the variables used in this table are also presented in the Appendix. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively.

the 1 % level.[6] In terms of the economic magnitude of peer effect, a one standard deviation increase in peers' organisation capital is associated with an increase in firms' organisation capital by 2 % (0.0251 × 0.8007). In terms of the unconditional mean value, this represents a 2.71 % contribution (0.1436/0.7416). This result reveals that peer firms' organisation capital influences the focal firm's organisation capital, and provides significant evidence of peer effect on the organisation capital of firms.

5.3.2. Instrumental variable regressions

Table 4 also reports the standard instrumental variable regression and the Lewbel (2012) approach (as discussed in Section 3.2), respectively (see Columns (2) and (3)). To support the relevance of our proposed instrumental variable, p_ui_{t-1}, we present an analysis that demonstrates how our instrumental variable is related to the variables that are important determinants of organisation capital. Put differently, we examine whether our instrumental variable measure contains information about contemporaneous or future firm *i*'s characteristics. Table 5 presents the estimation results that relate peer unemployment insurance benefits to firm-specific and peer firms' average characteristics. For a one-period-lag, Column (1), we find very low correlations of −0.0028 and 0.0120 for the relationship between peer unemployment insurance benefits and firm-specific characteristics. For a one-period lead, Column (2), we observe similar results. That is, the correlations

Table 5
Peer unemployment insurance benefits.

	p_ui_{t-1}		p_ui_{t-1}
Variables	(1)	Variables	(2)
roa_{t-1}	−0.0011	roa_t	−0.0084
	0.009		*0.008*
$fsize_{t-1}$	0.0025*	$fsize_t$	0.0034**
	0.001		*0.001*
mb_{t-1}	0.0029***	mb_t	0.0017***
	0.001		*0.001*
age_{t-1}	0.0120***	age_t	0.0090***
	0.003		*0.003*
sg_{t-1}	−0.0028***	sg_t	−0.0036***
	0.001		*0.001*
Control variables for peer firms	Yes	Control variables for peer firms	Yes
Year effects	Yes	Year effects	Yes
R^2	0.6522	R^2	0.6551

This table presents the estimation results relating the peer unemployment insurance (*p_ui*) benefits to firm-specific and peer firms' average characteristics. Firm size (*fsize*) is measured by natural logarithm of total assets. Market-to-book ratio (*mb*) is measured by market value of assets divide by total assets. Profitability (*roa*) is measured by operating income before depreciation divide by total assets. Sales growth (*sg*) is measured by natural logarithm of difference between the current and the prior level of sales, scaled by the prior level of sales. Firm age (*age*) is measured by natural log of the difference between the first year the firm appears in CRSP and the current year. Robust standard errors (in *italic*) are clustered at the firm level. The definitions of the variables used in this table are presented in the Appendix. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively.

[6] As a robustness check, we also adopt a larger TNIC dataset which is calibrated to be granular as two-digit SIC codes. Using a larger TNIC dataset, we find similar (untabulated) results from fixed effects regression. The coefficient on *p_oc_ep_ta* (0.0272) remains positive and statistically significant at the 1 % level.

between peer unemployment insurance benefits and firm-specific characteristics range between −0.0084 and 0.0090. These small economic magnitudes of the coefficient estimates make their effects tenuous. Thus, the peer firm unemployment insurance benefits contain less significant information related to firm *i*'s current or one-year-lag observable organisation capital determinants. These results are consistent with those of Leary and Roberts (2014), that the exclusion restrictions are not violated in our case, and highlight the reliability of the unemployment insurance benefits as an instrument used to estimate the *2sls* regression.

Columns (2) and (3) of Table 4 show the second-stage regression results obtained from the 2*sls* estimation of peer effect on organisation capital. Using the instrumental variable of peer unemployment insurance benefits (p_ui_{t-1}), the estimated results are reported in Column (2) of Table 4. In the untabulated results, the coefficient on *p_ui* is significant at the 1 % level in the first-stage regression. In Column (2) of Table 4, the *p*-value of Cragg-Donald's Wald F weak-instrument test statistic is 0.000, indicating rejection of the null hypothesis that the instruments are weak. Importantly, we find that the estimated coefficient for peer firm organisation capital (*p_oc_ep_ta*) is positive (0.1794), and significantly associated with focal firm organisation capital. In terms of the economic magnitude of peer effect, a one standard deviation increase in peers' organisation capital is associated with an increase in firms' organisation capital by 14.36 % (0.1794 × 0.8007). In terms of the unconditional mean value, this represents a 19.37 % contribution (0.1436/0.7416).

In Column (3) of Table 4, we employ the instrumental variable method developed by Lewbel (2012). The under-identification test is significant at the 1 % level, indicating that the instrument is relevant. Additionally, the weak identification test shows that the instruments are correlated with our endogenous regressors, given the Cragg-Donald's Wald F weak-instrument test statistic is greater than the Stock & Yogo (2005) critical value. These statistics further provide validity for the selected instruments. Importantly, the estimated result from second-stage regression shows that the coefficient for peers' organisation capital (0.0365) is positive and statistically significant at the 1 % level.[7] These results provide strong evidence of peer influence on organisation capital. In terms of the economic magnitude of peer effect, a one standard deviation increase in peers' organisation capital is associated with an increase of firms' organisation capital by 2.92 % (0.0365 × 0.8007). In terms of the unconditional mean value, this represents 3.94 % (0.0292/0.7416). Taken together, in the second-stage of the 2*sls* regressions, we find that the coefficients for peer firms' organisation capital are significantly positive, and the magnitude of the peer effect is larger than it was using the fixed effect regression. The peer effect on organisation capital is both statistically significant and economically substantial. Consistent with our expectation, we find evidence suggesting that there is significant peer influence on focal firm organisation capital.

5.4. Industry competition

According to the rivalry-based theory, mimicking the organisation capital of peer firms is expected to be more pronounced in more competitive industries. We explore whether mimicking behaviour is stronger for firms in more competitive industries using two proxies of product market competition. First, we use the concentration measure of Hoberg and Phillips (2016), denoted as *HHI-TNIC3*, which is measured using web crawling and text parsing algorithms of firms' annual 10-Ks filed with the SEC. We partition the sample into high (low) market competition if the firm is below (above) the median *HHI-TNIC*. By construction, a higher (lower) score for *HHI-TNIC3* indicates greater market power (market competition). The second proxy is the measure of *similarity* obtained from Hoberg and Phillips (2016) that captures the degree of product market similarity. The higher (lower) score for similarity indicates greater (lesser) market competition. We re-run the 2*sls* regression using peer unemployment insurance benefits (*p_ui*) as the instrumental variable, as well as the instrumental variable method developed by Lewbel (2012), with the same control variables as in previous models for these estimations. For brevity, we do not report the results for all the variables used in the 2*sls* regression.

Table 6 presents the estimated results obtained from the second-stage regression results of 2*sls* regression. For low competitive industries, in Columns (3), (4), (7) and (8), the coefficients on *p_oc_ep_ta* reported are insignificant. In Columns (1), (2), (5) and (6) of Table 6, the coefficients on *p_oc_ep_ta* are positive and statistically significant in highly competitive industries, regardless of whether instrumental variables estimation or the Lewbel (2012) estimation method is used. That is, the coefficients of 0.0884 (in Column (1)), 0.1235 (in Column (2)), 0.0999 (in Column (5)), and 0.0601 (in Column (6)) on *p_oc_ep_ta* are positive and statistically significant. These positive coefficients highlight the finding that peer influence is significant in an environment with strong market competition. Furthermore, the statistics obtained from the under-identification and weak identification tests provide validity for the selected instruments. One may argue that, in Column (6), the Hansen's J over-identification test statistic is significant at the 5 % level, indicating a rejection of the null hypothesis of valid instruments. Hansen J statistic is known to have over-rejection issue in the econometric literature (Guggenberger & Kumar, 2012). We argue that the null hypothesis of valid instruments cannot be strongly rejected at the 5 % level.

Overall, these results are consistent with the proposition that organisation capital is used to compete in less concentrated industries. According to the rivalry-based theory of mimicking behaviour (Lieberman & Asaba, 2006), a firm imitates its peers to maintain competitive parity or to limit rivalry. A firm's organisation capital confers a competitive edge over peers which, in turn, builds up the ability to bargain and compete in the product market through nurturing firm performance, productivity and innovation (Eisfeldt & Papanikolaou, 2013; Francis et al., 2021). Our results are consistent with the rivalry-based theory of imitation, and suggest that peer influence increases with product market competition. That is, intense competition in the product market pressures a firm to adopt a corporate decision in response to the action of its peers. Fierce competitive pressure in the product market leads to mimicking behaviour which, in turn, enables firms to deal with rivals' aggressive actions (Cao, Liang, & Zhan, 2019; Liu & Wu, 2016).

5.5. Information environment

If organisation capital mimicking is motivated by information, we expect an increase in peer effect in environments with more information asymmetry. Following Gyimah et al. (2020) and Adhikari and Agrawal (2018), we employ two proxies for information environment. First, we use the probability of informed trading measure of Brown and Hillegeist (2007), denoted as *pin*, which measures information asymmetry between firms and investors. Owing to the availability of the *pin*, the sample for analysis is constrained to 19,929 firm-year observations. We partition the sample into a high (low) *pin* if the firm is below (above) the median *pin*. By construction, a higher (lower) *pin* reflects a poorer (better) quality of financial disclosure, that is, a higher (lower) level of information asymmetry. The second proxy is the number of financial analysts following the firm. Financial analysts are among the most important information producers in financial markets, and several studies highlight financial analysts as an important channel through

[7] Similarly, when using a larger TNIC dataset (which is calibrated to be granular as two-digit SIC codes), we find supportive evidence. When employing the instrumental variable method developed by Lewbel (2012), the coefficient on *p_oc_ep_ta* (0.0312) is positive and statistically significant at the 5 % level. These results suggest that the evidence of peer effects are generally robust, regardless of whether TNIC calibrated to be granular as two-digit or three-digit SIC codes are used.

Table 6
Industry competition and peer effect.

	High industry competition (Low *HHI-TNIC3*)		Low industry competition (High *HHI-TNIC3*)		High industry competition (High *similarity*)		Low industry competition (Low *similarity*)	
Variable:	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
p_oc_ep_ta	0.0884*	0.1235***	1.1061	0.0593	0.0999*	0.0601*	2.8608	0.2444
	0.053	*0.042*	*1.322*	*0.085*	*0.060*	*0.034*	*5.918*	*0.2302*
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,308	16,308	16,308	16,308	16,313	16,313	16,313	16,313
F-test: (1) versus (3)	3.29*							
F-test: (2) versus (4)		2.76*						
F-test: (5) versus (7)					4.49**			
F-test: (6) versus (8)						3.33*		
Under-identification test (Chi^2 p-value)	0.0000	0.0000	0.3456	0.0178	0.0000	0.0000	0.6240	0.3725
Weak identification test (Cragg-Donald Wald F statistic)	166.042	439.099	1.143	134.066	174.753	412.791	0.415	33.367
Over-identification test (Chi^2 p-value)	Not applicable	0.2314	Not applicable	0.0176	Not applicable	0.0200	Not applicable	0.0469

This table presents the second-stage regression results. The sample is partitioned into high (low) market competition if the firm is above (below) the median Herfindahl–Hirschman index (*HHI-TNIC3*) and product similarity (*similarity*). Robust standard errors (in *italic*) are clustered at the firm level and the confidence sets control coverage distortion without assuming the data are homoscedastic. The definitions of the variables used in this table are presented in the Appendix. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively.

which information related to a firm is revealed to the public (Adhikari, 2016; Kelly & Ljungqvist, 2012). Thus, a higher (lower) analyst following indicates a better (poorer) information environment. We partition the estimated results based on the proxies for industry environment, and estimate 2*sls* regressions similar to Table 6.

Table 7 presents the estimated results obtained from the second-stage regression results of 2*sls* estimation using the peer unemployment insurance benefits (*p_ui*) as the instrumental variable and the instrumental variable method developed by Lewbel (2012). In Columns (1), (2), (5) and (6) of Table 7, where estimated results for high information asymmetry are reported, the coefficients on *p_oc_ep_ta* are positive and statistically significant, regardless of whether the instrumental variables estimation or the Lewbel (2012) estimation method is used. The coefficients of 0.4388 (in Column (1)), 0.0341 (in Column (2)), 0.5145 (in Column (5)), and 0.0520 (in Column (6)) on *p_oc_ep_ta* are positive and statistically significant. These positive coefficients highlight that peer influence is significant in an environment with high information asymmetry. In the subgroups of environments with low information

Table 7
Information asymmetry and peer effect.

	High information asymmetry (High *pin*)		Low information asymmetry (Low *pin*)		High information asymmetry (Low *analyst*)		Low information asymmetry (High *analyst*)	
Variable:	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach	Instrumental variable regression	Lewbel (2012) approach
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
p_oc_ep_ta	0.4388*	0.0341*	0.1393*	0.0256	0.5145**	0.0520*	−0.0126	0.0430***
	0.231	*0.018*	*0.071*	*0.016*	*0.255*	*0.030*	*0.090*	*0.016*
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9949	9949	9980	9980	16,342	16,284	16,342	16,284
F-test: (1) versus (3)	2.74*							
F-test: (2) versus (4)		0.17						
F-test: (5) versus (7)					3.43*			
F-test: (6) versus (8)						0.97		
Under-identification test (Chi^2 p-value)	0.0000	0.0000	0.0034	0.0000	0.0013	0.0000	0.0000	0.0000
Weak identification test (Cragg-Donald Wald F statistic)	41.820	487.136	8.966	618.136	12.282	277.486	46.347	609.147
Over-identification test (Chi^2 p-value)	Not applicable	0.5762	Not applicable	0.8985	Not applicable	0.9170	Not applicable	0.7979

This table presents the second-stage regression results. The sample is partitioned into high (low) information asymmetry if the firm is above (below) the median probability of information trading (*pin*) and number of analysts (*analyst*). Robust standard errors (in *italic*) are clustered at the firm level and the confidence sets control coverage distortion without assuming the data are homoscedastic. The definitions of the variables used in this table are presented in the Appendix. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively.

Table 8
Alternative measures of organisation capital.

Panel A: Analysis of variance	*oc_ta*	
Industry component:	0.0184	
Firm component:	0.0337	
Error component:	0.0173	
Panel B: peers effect	Instrumental variable regression	Lewbel (2012) approach
Variable:	*oc_ta*	*oc_ta*
p_oc_ta	1.3302*	0.9965***
	0.685	*0.309*
Control variables	Yes	Yes
Year effects	Yes	Yes
Firm effects	Yes	Yes
Observations	32,626	32,626
Under-identification test (Chi^2 *p*-value)	0.0194	0.0034
Weak identification test (Kleibergen-Paap rk Wald F-stat)	15.801	98.591
Over-identification test (Chi^2 p-value)	Not applicable	Not applicable

Using an alternative measure of Peters and Taylor (2017), Panel A shows the estimated results obtained from the analysis of variance (ANOVA) which decomposes the variance of organisation capital into three components: industry variance, firm variance and error variance. Panel B presents the second stage regression analysis of organisation capital peer effect. Robust standard errors (in *italic*) are clustered at the firm level and the confidence sets control coverage distortion without assuming the data are homoscedastic. The definitions of the variables used in this table are presented in the Appendix. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively.

asymmetry (in Columns (3), (4), (7) and (8)), some coefficients on *p_oc_ep_ta* appear to be negative or insignificant. More importantly, the magnitudes of the coefficients in the subgroups of environments with high information asymmetry are consistently larger than the estimated coefficients reported in the subgroups of environments with low information asymmetry, which allows us to gain confidence that imitation is more pronounced in an environment with high information asymmetry. Overall, these results shed light on the importance of the information environment for peer effect, and imitation increases in a poorer information environment. In line with the information-based theory (Lieberman & Asaba, 2006), our findings illuminate the evidence on the impact of peer information disclosures on a firm's decisions.

5.6. Robustness check

We next re-estimate both ANOVA and Eq. (1) using the organisation capital measure of Peters and Taylor (2017) as an alternative measure of organisation capital (*oc_ta*). Estimate results are reported in Table 9. In Panel A of Table 8, we estimate the analysis of variance by decomposing the variance of organisation capital into three components (industry variance, firm variance, and error variance), and observe results similar to those in Table 3. That is, we observe that the variance components at the industry and firm levels are 0.0184, and 0.0337, respectively. Given the total variance is 0.0693, the industry component accounts for 26.51 % of the total variance, reflecting that one-quarter of the variation in organisation capital is due to industry variations. Consistent with Table 3, the result highlights the importance of the industry-level component in determining firms' organisation capital.

In Panel B of Table 8, using the instrumental variable regression, the second-stage regression yields a positive and statistically significant coefficient of 1.3302 on peers' organisation capital (*p_oc_ta*) in predicting a firm's own organisation capital. Specifically, the coefficient estimate reflects that an increase in peers' organisation capital by 10 % leads a firm to increase its own organisation capital by about 13.3 %. Similarly, when the Lewbel approach estimation method is used, the second-stage regression shows a coefficient of 0.9965 on peers' organisation capital (*p_oc_ta*), which is positive and statistically significant at the 1 % level. This coefficient estimate indicates that an increase in peers' organisation capital by 10 % leads a firm to increase its own organisation capital by about 9.965 %. Taken together, our findings provide further evidence that mimicking behaviour is not driven by any specific measure of organisation capital.[8]

6. Conclusion

Organisation capital is one of the most valuable type of intangible capital embodied in key talent, and provides firms with sustainable comparative advantages, such as efficient production and superior performance. This paper attempts to highlight the important role of industry-level determinant(s) in determining organisation capital, and furthers the knowledge of whether firms mimic their peers in formulating organisation capital, given that mimicking peers' organisation capital can be an essential tool to enhance a firm's product market competitiveness and signal its quality to the public.

Using 32,626 firm-year observations over the period 1996 to 2017, we show evidence that industry-level component plays a role in determining firms' organisation capital. More specifically, about one quarter of the variation in organisation capital is due to industry variation. In addition, we find strong evidence that the investment in organisation capital of its peers is a determinant of the firm's organisation capital. We provide one explanation for this finding, namely peer pressure. Our cross-sectional analyses show that peer influence on organisation capital is consistent with both the rivalry-based theory and the information-based theory of imitation. We find that peer influence is stronger among firms that operate under high product market competition and in environments with high levels of information asymmetry. Our estimated results are robust to alternative measures of organisation capital, and remain robust, after accounting for endogeneity issues.

This study contributes to an emerging literature exploring the importance of peer pressure on firms' intangible capital, and provides important implications for research in finance. We find that learning from peers matters for investing in organisation capital. If industry peers play a significant role when firms are making their decisions, managers may not have as much discretion in determining firm policies as the research on managerial behaviour suggests. From the perspective of regression estimation, the presence of a significant association between organisation capital across firms within the industry highlights the importance of clustering standard errors at the industry level when analysing firm-level organisation capital.

Data availability

No

Acknowledgements

We thank the participants at the seminars at City University of Macau and Curtin University, for helpful comments and suggestions provided on earlier versions of this manuscript. Any errors are my own.

[8] One may argue that the peer effect could be driven by the significant representation of certain industries, thus we re-estimate Equation (1) excluding the Business Services, Electronic Equipment, and Petroleum and Natural Gas industry. We find evidence that our main finding is not driven by these specific industries.

Appendix A

Details of the variables constructed for analyses.

Variable	Definition	Source
oc_ta	Organisation capital estimated by Peters and Taylor (2017) scaled by total assets (item AT)	WRDS (Peters and Taylor Total Q)
oc_ep_ta	Organisation capital following Eisfeldt and Papanikolaou (2013) scaled by total assets (item AT)	Compustat
p_oc_ta	Average organisation capital estimated by Peters and Taylor (2017) of TNIC-based peers, excluding firm *i*	WRDS (Peters and Taylor Total Q)
p_oc_ep_ta	Average organisation capital following Eisfeldt and Papanikolaou (2013) of TNIC-based peers, excluding firm *i*	Compustat
Control variables:		
Firm size (*fsize*)	Natural logarithm of total assets (item AT)	Compustat
Market-to-book ratio (*mb*)	Market value of assets (item PRCC_F multiplied by item CSHO plus item AT minus item CEQ), scaled by total assets (AT)	Compustat
Profitability (*roa*)	Operating income before depreciation (item OIBDP), scaled by total assets (item AT)	Compustat
Sales growth (*sg*)	Natural logarithm of difference between the current and the prior level of sales (item SALE), scaled by the prior level of sales	Compustat
Firm age (*age*)	The natural log of the difference between the first year the firm appears in CRSP and the current year	Compustat
Variables for further analyses:		
HHI-TNIC3	Market competition estimated by Hoberg and Phillips (2016)	Hoberg and Phillips (2016)
similarity	Product similarity estimated by Hoberg and Phillips (2016)	Hoberg and Phillips (2016)
Probability of informed trading (*pin*)	Probability of informed trading estimated by Brown and Hillegeist (2007)	Brown and Hillegeist (2007)
Analyst coverage (*analyst*)	The number of financial analysts following the firm	I/B/E/S
tobin Q	Market value of total asset (item: AT – CEQ + CSHO × PRCC_F), scaled by total assets (item AT)	Compustat
Leverage (*lev*)	The sum of debt in current liabilities (item DLC) and total long-term debt (item DLTT), scaled by total assets (item AT)	Compustat
Research intensity (*id_int*)	Research and development expense (item XRD), scaled by sale (item SALE)	Compustat

References

Adhikari, B. K. (2016). Causal effect of analyst following on corporate social responsibility. *Journal of Corporate Finance, 41*, 201–216.

Adhikari, B. K., & Agrawal, A. (2018). Peer influence on payout policies. *Journal of Corporate Finance, 48*, 615–637.

Anh Do, V. P., & Bui, Q. T. (2022). The influence of leadership personality on profitability and firm investment in human capital: The case of Vietnamese SMEs. *Finance Research Letters, 47*, Article 102960.

Asad, A.-R., Boubaker, S., & Dang, V. A. (2021). Is there mimicking behavior in firms' trade credit decisions? *Review of Corporate Finance, 1*(1–2), 81–134. https://doi.org/10.1561/114.00000003

Atkeson, A., & Kehoe, P. J. (2005). Modeling and measuring organization capital. *Journal of Political Economy, 113*, 1026–1053.

Attig, N., & Cleary, S. (2014). Organizational capital and investment-cash flow sensitivity: The effect of management quality practices. *Financial Management, 43*, 473–504.

Blanco-Mazagatos, V., de Quevedo-Puente, E., & Delgado-García, J. B. (2018). Human resource practices and organizational human capital in the family firm: The effect of generational stage. *Journal of Business Research, 84*, 337–348.

Brown, S., & Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies, 12*, 443–477.

Cao, J., Liang, H., & Zhan, X. (2019). Peer effects of corporate social responsibility. *Management Science, 65*, 5487–5503.

Cao, S. S., Fang, V. W., & Lei, L. (2021). Negative peer disclosure. *Journal of Financial Economics, 140*, 815–837.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*, 57–82.

Chen, D., Liu, M., Ma, T., & Martin, X. (2017). Accounting quality and trade credit. *Accounting Horizons, 31*, 69–83.

Chen, W., & Inklaar, R. (2016). Productivity spillovers of organization capital. *Journal of Productivity Analysis, 45*, 229–245.

Corrado, C., Haskel, J., & Jona-Lasinio, C. (2017). Knowledge spillovers, ICT and productivity growth. *Oxford Bulletin of Economics and Statistics, 79*, 592–618.

Corrado, C., Hulten, C., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth, 55*, 661–685.

Eisfeldt, A. L., & Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *The Journal of Finance, 68*, 1365–1406.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics, 43*, 153–193.

Fortin, B., & Ragued, S. (2017). Does temporary interruption in postsecondary education induce a wage penalty? Evidence from Canada. *Economics of Education Review, 58*, 108–122.

Foucault, T., & Fresard, L. (2014). Learning from peers' stock prices and corporate investment. *Journal of Financial Economics, 111*, 554–577.

Francis, B., Mani, S. B., Sharma, Z., & Wu, Q. (2021). The impact of organization capital on firm innovation. *Journal of Financial Stability, 53*, Article 100829.

Francis, B. B., Hasan, I., & Kostova, G. L. (2016). When do peers matter?: A cross-country perspective. *Journal of International Money and Finance, 69*, 364–389.

Gao, M., Leung, H., & Qiu, B. (2021). Organization capital and executive performance incentives. *Journal of Banking & Finance, 123*, Article 106017.

Goodridge, P., Haskel, J., & Wallis, G. (2017). Spillovers from R&D and other intangible investment: Evidence from UK industries. *Review of Income and Wealth, 63*, S22–S48.

Grennan, J. (2019). Dividend payments as a response to peer influence. *Journal of Financial Economics, 131*, 549–570.

Guggenberger, P., & Kumar, G. (2012). On the size distortion of tests after an overidentifying restrictions pretest. *Journal of Applied Econometrics, 27*, 1138–1160.

Gyimah, D., Machokoto, M., & Sikochi, A. (2020). Peer influence on trade credit. *Journal of Corporate Finance, 64*, Article 101685.

Hasan, M. M., & Cheung, A. (2018). Organization capital and firm life cycle. *Journal of Corporate Finance, 48*, 556–578.

Hasan, M. M., & Cheung, A. (2023). Organization capital and firm risks. *China Accounting and Finance Review, 25*, 338–367.

Hasan, M. M., Lobo, G. J., & Qiu, B. (2021). Organizational capital, corporate tax avoidance, and firm value. *Journal of Corporate Finance, 70*, Article 102050.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy, 124*, 1423–1465.

Jory, S. R., Khieu, H. D., Ngo, T. N., & Phan, H. V. (2020). The influence of economic policy uncertainty on corporate trade credit and firm value. *Journal of Corporate Finance, 64*, Article 101671.

Kelly, B., & Ljungqvist, A. (2012). Testing asymmetric-information asset pricing models. *The Review of Financial Studies, 25*, 1366–1413.

Khoo, J., & Cheung, A. (2023). The hidden cost of organisation capital: Evidence from trade credit. *The British Accounting Review, 101238*.

Kim, H.-D., Park, K., & Song, K. R. (2021). Organization capital and analysts' forecasts. *International Review of Economics & Finance, 71*, 762–778.

Leary, M. T., & Roberts, M. R. (2014). Do peer firms affect corporate financial policy? *The Journal of Finance, 69*, 139–178.

Lev, B., & Radhakrishnan, S. (2005). Measuring Capital in the new Economy. In C. Carol, H. John, & S. Daniel (Eds.), *The valuation of organization capital* (pp. 73–110). University of Chicago Press.

Lev, B., Radhakrishnan, S., & Zhang, W. (2009). Organization Capital. *Abacus, 45*, 275–298.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate Mismeasured and endogenous Regressor models. *Journal of Business & Economic Statistics, 30*, 67–80.
Li, K., Qiu, B., & Shen, R. (2018). Organization capital and mergers and acquisitions. *Journal of Financial and Quantitative Analysis, 53*, 1871–1909.
Li, P., Li, F. W., Wang, B., & Zhang, Z. (2018). Acquiring organizational capital. *Finance Research Letters, 25*, 30–35.
Lieberman, M. B., & Asaba, S. (2006). Why Do firms imitate each other? *Academy of Management Review, 31*, 366–385.
Lin, C., Lin, P., Song, F. M., & Li, C. (2011). Managerial incentives, CEO characteristics and corporate innovation in China's private sector. *Journal of Comparative Economics, 39*, 176–190.
Liu, S., & Wu, D. (2016). Competing by conducting good deeds: The peer effect of corporate social responsibility. *Finance Research Letters, 16*, 47–54.
Machokoto, M., Gyimah, D., & Ntim, C. G. (2021). Do peer firms influence innovation? *The British Accounting Review, 53*, Article 100988.
Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies, 60*, 531–542.
Marwick, A., Hasan, M. M., & Luo, T. (2020). Organization capital and corporate cash holdings. *International Review of Financial Analysis, 68*, Article 101458.
Millimet, D. L., & Roy, J. (2016). Empirical tests of the pollution haven hypothesis when environmental regulation is endogenous. *Journal of Applied Econometrics, 31*, 652–677.
Pennings, J. M., Lee, K., & Van Witteloostuijn, A. (1998). Human capital, social capital, and firm dissolution. *Academy of Management Journal, 41*, 425–440.
Peters, R. H., & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics, 123*, 251–272.
Regier, M., & Rouen, E. (2023). The stock market valuation of human capital creation. *Journal of Corporate Finance, 79*, Article 102384.
Ross, J.-M., & Sharapov, D. (2015). When the leader follows: Avoiding dethronement through imitation. *Academy of Management Journal, 58*, 658–679.
Stock, J. H., & Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. In DWK Andrews, & JH Stock (Eds.), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 80–108). Cambridge: Cambridge University Press.
Sun, X., Li, H., & Ghosal, V. (2020). Firm-level human capital and innovation: Evidence from China. *China Economic Review, 59*, Article 101388.
Venieris, G., Naoum, V. C., & Vlismas, O. (2015). Organisation capital and sticky behaviour of selling, general and administrative expenses. *Management Accounting Research, 26*, 54–82.