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Organization capital effect in stock returns—The role of R&D

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Abstract

Previous studies document a strong organization capital effect in stock returns. We investigate whether and how research and development (R&D) activities affect this organization capital effect. We find that the organization capital effect is stronger in firms with R&D activities. The annual abnormal return of the hedge portfolio sorted by organization capital is 2.41% for R&D firms but only 0.41% for non-R&D firms. Further analyses show that the organization capital effect can be attributed to R&D characteristics rather than R&D risk factors.

KEYWORDS
intangible assets, organization capital, R&D, stock return

JEL CLASSIFICATION
G12, O32

1 | INTRODUCTION

The importance and real impact of intangible assets have been extensively studied over the past few decades.[1] Intangible assets encompass all non-physical assets specifically owned by a firm, among which are included organization capital and research and development (R&D). Organization capital refers to the accumulation of firm-specific information that enhances production efficiency (Prescott & Visscher, 1980), while R&D has long been recognized as a major driving force of economic growth (Brown et al., 2009). Meanwhile, a rich literature documents that R&D has positive predictive power for future stock returns (L. K. Chan et al., 2001; Lev & Sougiannis, 1996). Eisfeldt and Papanikolaou (2013) first document the return predictability of organization capital. However, unlike R&D, the driving forces of the

[1] See, for example, Corrado et al. (2009), Ai et al. (2013), Peters and Taylor (2017) and McGrattan (2017).

return predictability of organization capital are not extensively explored. As noted by Green et al. (2017), whether a firm characteristic provides an independent source of information about return predictability is critical. Therefore, the purpose of this paper is to investigate to what extent the newly developed asset pricing effect of organization capital is related to the well-known R&D effect.

Organization capital facilitates a firm's use of its culture, structure and systems as sources of competitive advantage in its product market (Martín-de-Castro et al., 2006; Nahapiet & Ghoshal, 1998). Specifically, organization capital consists of systems and processes employed in the firm's operating activities and the incentive compensation that motivates a firm's human resources (Lev & Radhakrishnan, 2005).[2] Eisfeldt and Papanikolaou (2013) further treat organization capital as a factor that is embodied in a firm's key personnel. They argue that from the shareholders' perspective, higher organization capital entails greater risk to the firm and thus is associated with higher expected returns.[3] They find a 4.18% annual abnormal return on a long-short portfolio sorted by organization capital based on US data between 1970 and 2008.

In the current technology- and knowledge-oriented economy, firms develop their own niche by increasing contributions to R&D activities. Brown et al. (2009) report that R&D activities have been growing since 1980s in the United States. According to the Organization for Economic Co-operation and Development (OECD), gross domestic spending on R&D in the United States in 2017 was triple the 1981 figure.[4] Lev and Sougiannis (1996) document a significant intertemporal relationship between the R&D capital and stock returns. L. K. Chan et al. (2001) further report a positive relationship between the R&D intensity and excess stock returns.[5] In general, previous studies attribute the positive R&D-return relationship to either risk compensation or mispricing.[6]

The organization capital effect in stock returns can be related to the R&D effect because organization capital and R&D share common fundamental concepts and major features. First, they both are significant components of the intangible assets of firms. Organization capital and R&D account for nearly 30% and 16% of intangible assets, respectively, in the United States (Corrado et al., 2009).[7] Moreover, the underlying constituents of organization capital and R&D are overlapping. Conceptually, organization capital includes the value incorporated in the knowledge of key personnel such as executives and technical professionals (Eisfeldt & Papanikolaou, 2013). The key personnel are not restricted to top executives only but also can include R&D staff and middle-level managers. R&D investments represent expenditures on experimental processes and salaries to the highly skilled technicians and researchers. As R&D activities are initiated by technical professionals and skilled workers, and some R&D expenditures comprised wage payments to them, we contend that organization capital coincides with the driving force of R&D activities (Belo et al., 2017; Brown et al., 2009; Francis et al., 2021). In particular, engineers and technicians tend to have high labor mobility (Almeida & Kogut, 1999; Saxenian, 1994). While Eisfeldt and Papanikolaou (2013) suggest that the movement of key employees drives the stock returns of organization capital, the high mobility of R&D people could enlarge the asset

[2] Specific examples of organization capital include the following: (i) Cisco's Internet-based product installation and maintenance system, which is estimated by Cisco's chief financial officer (CFO) to have saved $1.5 billion over 3 years (*Economist*, June 26, 1999); (ii) Amazon's customer recommendation system that customizes the experience for the returning customer, which boosted 29% sales increase in its second quarter (*Fortune*, July 30, 2012); and (iii) Zappos' outstanding customer service, which has contributed to the foundation of the $1.2 billion acquisition proposed by Amazon (*Forbes*, May 11, 2015).

[3] This implication relies on two essential characteristics of organization capital. First, key talent, known as a highly specialized labor input, is movable across firms. Second, the efficiency of organization capital is specific to a firm. More specifically, as key talent has the option to leave the firm, such employees can claim compensation from shareholders equal to the option value, which is determined by the efficiency of organization capital in the new firms. The required compensation rises when the outside option improves, that is, when there is an outside shock that increases the new firms' efficiency of organization capital. Since the outside option for key talent exposes firm shareholders to additional systematic risk, they require higher expected returns.

[4] OECD (2019), Gross domestic spending on R&D (indicator). doi: 10.1787/d8b068b4-en

[5] Studies have documented that R&D is positively related to firm performance and stock returns. See Lev and Sougiannis (1996), Chambers et al. (2002), L. K. Chan et al. (2001), Eberhart et al. (2004), Hsu (2009), D. Li (2011), Donelson and Resutek (2012), Cohen et al. (2013), K. Chan et al. (2015) and Lin and Wang (2016).

[6] R&D activities are risky in that firms raise funds (either internally or externally) to conduct R&D activities, which could end up with no substantial results. As a result, firms engaging in R&D activities earn higher returns for bearing R&D-related risks (Chambers et al., 2002; D. Li, 2011). Despite this, R&D tends to be undervalued, and thus hedge portfolios formed by firm R&D could earn abnormal returns (L. K. Chan et al., 2001; Cohen et al., 2013; Lev & Sougiannis, 1996).

[7] Bureau of Economic Analysis (2013). *Preview of the 2013 Comprehensive Revision of the National Income and Product Accounts.*

pricing effect of organization capital. This conjecture is also aligned with recent studies combining labor economics and asset pricing (Belo et al., 2017; Donangelo, 2014; Kuehn et al., 2017).[8]

In addition, we notice that to some extent, the measurement of organization capital incorporates R&D. Empirically, organization capital is measured as the accumulation of deflated value of selling, general and administrative (SG&A) expenses (Eisfeldt & Papanikolaou, 2013, 2014; Lev & Radhakrishnan, 2005). Under accounting practices and the Compustat reporting traditions, however, quite a few R&D expenditures may be recognized under the subcategory of SG&A expenses. First, the generally accepted accounting principles rubric does require firms to separately disclose R&D expenses if they are material. Ball et al. (2015) observe that "if the amount (*of R&D expenses*) exceeds 1% of firm revenue, it must be disclosed (either as a separate line item on the Income Statement or in the Notes to the Accounts)."[9]

Second, to facilitate comparability across firms, Compustat defines its SG&A variable (*XSGA*) as the sum of firms' actual reported SG&A and expenditures on R&D even if firms report R&D expenses separately (Ball et al., 2015, 2016). Among our sample data, nearly 80% of firms covered in the Compustat database recognize R&D expenditures under the subcategory of SG&A. Therefore, from the perspective of empirical measurement, we contend that organization capital is related to R&D as well and conjecture that the effect of organization capital on stock returns can be attributed to R&D activities. More specifically, we hypothesize that the alpha associated with organization capital is higher for R&D firms than for non-R&D firms.

Our empirical evidence supports the hypothesis that the organization capital effect in stock returns is stronger for firms engaging in R&D activities.[10] We select US firms from 1970 to 2017 and measure organization capital based on Eisfeldt and Papanikolaou (2013). Using the Fama–French (2015) five-factor model, we first confirm that firms in the top organization capital quintile outperform those in the bottom quintile, a result consistent with Eisfeldt and Papanikolaou (2013). We then group our sample each year into firms with R&D expenses and those without. We show that the value-weighted (VW) hedge portfolio formed by buying the top organization capital quintile and selling the bottom quintile generates a significant annual alpha of 2.41% in firms with R&D activities but earns a non-significant alpha of 0.41% in firms without R&D. In other words, the significant organization capital effect in stock returns exists only in the R&D group. The return spread between extreme organization capital quintiles is almost trivial in the group without R&D. We perform a battery of robustness checks by applying different factor models, different weight schemes to compute portfolio returns and different sampling criteria. Our finding that the organization capital effect is much stronger in R&D firms holds in each of these robustness checks. We further explore the strong organization capital effect in the R&D group by forming an extreme hedge portfolio that buys stocks with high organization capital in the R&D group and sells stocks with low organization capital in the group without R&D. We find this extreme hedge portfolio earns a significant alpha of 7.18% on an annual basis.

These results drive us to wonder whether the organization capital effect is associated with the R&D risk factor. That is, the stock returns of organization capital may co-move with the risk premium associated with R&D investments. We follow previous papers (Al-Horani et al., 2003; Dedman et al., 2009; Gregory & Michou, 2009; Lin & Wang, 2016) and construct an R&D risk factor as the hedge portfolio sorted by R&D information. We examine the alphas of organization capital portfolios by adding the R&D risk factor into the Fama–French (2015) five-factor model. If the alpha of organization capital reflects the systematic risk of R&D, the R&D risk factor should be able to explain the documented organization capital effect. We find that the alpha of the hedge portfolio remains large under a number of

[8] These papers generally suggest that firms that are not sensitive to the labor market tightness experience higher stock returns in cross section. When the labor of such firms has high mobility, the labor market tends to have lower friction for labor movement.

[9] Similarly, US Securities and Exchange Commission Regulation 5-03.2 states that firms are not required to break out R&D expenses from SG&A expenses if they are less than 10% of SG&A (Billett et al., 2018; Gentry & Shen, 2013).

[10] Empirically, we sort firms into quintiles by organization capital relative to their industry peers. We long firms with more organization capital and short those with less organization capital and compute the VW hedge portfolio return. By extending the data to 2017, we document that the annual excess return of the hedge portfolio is about 3.27%, and the average annual alpha of the hedge portfolio is 2.36%, which is statistically consistent with Eisfeldt and Papanikolaou (2013). While one may wonder at the small alpha, Harvey et al. (2016), Hou et al. (2020), Linnainmaa and Roberts (2018) and Chordia et al. (2017) provide detailed discussion of the downscaling of alpha in general asset pricing papers.

specifications of the R&D factors, implying that the organization capital effect is not a compensation for firms bearing the risks of conducting R&D activities.

Next, we examine whether the organization capital effect is in part due to R&D-related firm characteristics, an idea in the spirit of Daniel and Titman (1997), Fama and French (2008), Cooper et al. (2010) and Conrad et al. (2013).[11] Using a two-factor model including the market index return and the organization capital factor, Eisfeldt and Papanikolaou (2013) document no significant alphas for all of five portfolios sorted by organization capital. Their results imply that the returns related to organization capital can be attributed to the co-movements between these portfolio returns and the organization capital factor. To further dissect the source of the alpha, we examine whether the returns sorted by organization capital and R&D can be explained by the organization capital factor. We sort cross-sectional returns independently by organization capital quintiles and an R&D dummy (equals one if the firm has R&D), and we find significant alphas in half of these 10 portfolios. A test of Gibbon et al. (1989) affirms that the regression intercepts for these portfolios are statistically different from zero. This analysis indicates that the R&D-related firm characteristics are possibly related to the alpha of organization capital.

Moreover, we perform Fama–MacBeth's (1973) cross-sectional return regressions. We find a significantly positive coefficient on organization capital in regressions after controlling for size, book-to-market ratio, asset growth and operating profitability. The coefficient on organization capital, however, is no longer significant when we use the VW least square method, indicating that the organization capital effect may largely be concentrated among small firms. The evidence is consistent with Green et al. (2017), who find that organization capital fails to predict cross-sectional stock returns when they use the VW least square method or exclude micro-cap firms in the Fama and MacBeth (1973) regressions.

To explore how the organization capital effect interacts with R&D, we examine the return predictability of *OC with R&D activity* and *OC without R&D activity* in the Fama and MacBeth (1973) regressions. The coefficients on *OC with (without) R&D activity* are significant (not significant) in both the equal-weighted (EW) and VW least square method, indicating that the organization capital effect is likely to be driven by R&D activities. Our results hold when we further control for momentum, leverage, illiquidity and financial constraint in the regressions.

Furthermore, we test whether the impact of R&D activities on the organization capital effect is related to labor mobility. The Uniform Trade Secrets Act (UTSA), also known as the law for trade secrets, prevents the leakage of non-public knowledge of the focal firm to its competitors, for example, through employee movement (Glaeser, 2018). As a result, firms in UTSA states have lower labor mobility.[12] Empirically, we document that the impact of R&D activity on the organization capital effect is more prominent when highly skilled employees possess greater labor mobility. That is, only when labor mobility exists can R&D activities positively affect organization capital effect in stock returns.

This paper contributes to several streams of literature. First, we complement the line of studies that examines the empirical relationship between intangible capital and stock returns. Ai et al. (2013) provide an equilibrium framework for the measurement of intangible capital, which requires a lower expected return than physical capital does under equilibrium. Peters and Taylor (2017) show that the *q*-theory helps explain intangible investment. McGrattan (2017) incorporates intangible investments into a multisector general equilibrium model, which can improve the measurement of total factor productivity. While recent papers emphasize the importance of intangible capital in assessing stock returns, this paper explores the key components of intangible capital: organization capital and R&D.

[11] Daniel and Titman (1997) contend that firm size and book-to-market ratio rather than the covariance structure drive the cross-sectional variation in stock returns. Fama and French (2008) demonstrate that many well-known anomalies exist only in certain types of stocks. Cooper et al. (2010) and Conrad et al. (2013) study asset pricing effects associated with corporate political contribution and *ex-ante* skewness, respectively, and argue that these effects are firm-specific and hard to explain by risk.

[12] In other words, for firms in the states with UTSA, their engineers and technical professionals cannot easily move to competitors. If the more profound organization effect in R&D firms is driven by labor mobility, the impact of R&D activities on the organization capital effect would be much weaker for firms in UTSA states.

Second, Cochrane (2011) and Green et al. (2017) challenge past papers and identify the firm characteristics that provide independent information about future return predictability by including multiple firm characteristics simultaneously. In particular, Green et al. (2017) find that R&D, but not organization capital, is a reliably independent return determinant. Our paper in part confirms their argument in two ways. First, we show that the annual abnormal return of the hedge portfolio sorted by organization capital is much lower for non-R&D firms than for R&D firms. The organization capital effect is significant only in firms with R&D. Second, when we examine *OC with R&D activity* and *OC without R&D activity* in the Fama and MacBeth (1973) regressions, only the *OC with R&D activity* significantly predicts cross-sectional stock returns. Collectively, our results suggest that organization capital effect is closely related to firms' R&D activities and that organization capital may not be an independent asset pricing factor.

Third, this paper explores our understanding of organization capital. Prescott and Visscher (1980) first propose the idea of organization capital, and Atkeson and Kehoe (2005) and Lev and Radhakrishnan (2005) further provide the model and measurement for organization capital. Using European firms, Tronconi and Marzetti (2011) show that organization capital is a crucial determinant of firm performance. Carlin et al. (2012) further document that firms with more organization capital have lower employee turnover and higher wages. Eisfeldt and Papanikolaou (2013, 2014) introduce organization capital as a production factor and argue that organization capital makes firms riskier. Thus, while previous papers have examined the real effect of organization capital, our paper further connects the organization capital effect in stock returns to R&D. Moreover, similar to K. Green et al. (2017), our study suggests that the organization capital effect appears to be more relevant to small firms. This finding is consistent with recent literature finding that high organization capital firms tend to be in the early and declining stages (Hasan & Cheung, 2018) and high organization capital firms, especially young and small acquirers, generate better post-merger stock returns (K. Li et al., 2018).[13] We also complement a recent paper by Yildirim and Allen (2021) who find that only the non-portable component of organization capital that excludes the top-executive compensations is associated with abnormal stock returns.[14] Our finding that the organization capital effect exists mainly in the R&D firms provides a venue to further dissect the return predictability of non-portable components in Yildirim and Allen (2021).

Fourth, this paper enriches the R&D literature. Lev and Sougiannis (1996) and the following papers—Chambers et al. (2002), L. K. Chan et al. (2001) and Eberhart et al. (2004)—document a positive relationship between R&D and stock returns. More recent papers further investigate the R&D return predictability across various dimensions (Cohen et al., 2013; Donelson & Resutek, 2012; D. Li, 2011; Lin & Wang, 2016). Our paper extends this line of study by arguing that R&D not only predicts stock returns but also affects the other pricing factor, organization capital.

Finally, our empirical results are aligned with recent studies combining labor economics and asset pricing (Belo et al., 2017; Donangelo, 2014; Kuehn et al., 2017). These papers suggest that labor market tightness is related to asset pricing. Our results indicate that firms with more skilled staff, who have high labor market mobility, are less sensitive to labor market tightness and experience higher stock returns in the cross-section.

The remainder of this paper is organized as follows. Section 2 presents our data and methodology. Section 3 demonstrates the empirical results. Section 4 discusses the role of the R&D-related risk and firm characteristics on organization capital effect. We conclude in Section 5.

[13] Our paper differs from Park (2022), who focuses on the predictability of intangible-adjusted book-to-market (B/M) ratio, as we focus purely on organization capital's the return predictability and its interaction/linkage between R&D activities. We follow Green et al.'s (2017) approach to perform both EW and VW Fama–MacBeth regressions, making our results directly comparable to Green et al. (2017) and offering an opportunity to reconcile Eisfeldt and Papanikolaou (2013) with the recent literature regarding the independence of predictability of organization capital (e.g., Cochrane, 2011; Feng et al., 2020; Green et al., 2017). Moreover, we investigate whether engineer turnover may affect organization capital effect, whereas Park (2022) does not provide any related channel tests.

[14] Yildirim and Allen (2021) decompose organization capital (OC) into two components: human capital OC (*HC_OC*) and strategic OC (*Strategic_OC*). *HC_OC* is portable and constructed by capitalizing total compensation of the top five executives. *Strategic_OC* is non-portable and constructed by capitalizing SG&A expenses that exclude top five executives' compensation. They empirically show that the systematic risk premium exists only in the S*trategic_OC* component, especially for firms with greater information asymmetry or poor corporate governance.

2 | DATA AND METHODOLOGY

In this section, we first demonstrate how we filter the data and construct the sample. Next, we show how we measure organization capital and illustrate the methodology used in the empirical tests. Finally, we present the summary statistics of our sample.

2.1 | Data

We start our sample with all firms listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotations (NASDAQ) and restrict our sample firms to domestic and ordinary common shares. We follow Eisfeldt and Papanikolaou (2013) and exclude financial firms, which are firms with Standard Industrial Classification (SIC) code from 6000 to 6799, and restrict the sample to firms with December fiscal year and non-missing SIC codes.[15] We retrieve accounting data from Compustat and market data from the Center for Research in Securities Prices (CRSP). We start our sample in 1970 and end it in 2017. The sample consists of 78,452 firm-year observations and an average of 1705 firms per year.

2.2 | Methodology

We measure the organization capital of each firm in accordance with Eisfeldt and Papanikolaou (2013). Similar to the methodology used by the Bureau of Economic Analysis (BEA) to construct a stock of R&D capital, organization capital (OC_{it}) is the sum of its own depreciated value in the previous period and the contemporary deflated SG&A expenses,

$$OC_{it} = (1 - \delta_0)\ OC_{it-1} + \frac{SGA_{i,t}}{cpi_t}, \tag{1}$$

where $SGA_{i,t}$ denotes the SG&A expenses of firm i in year t, cpi_t denotes the consumer price index and δ_0 is the depreciation rate. We retrieve the consumer price index from the US Bureau of Labor Statistics.[16] The depreciation rate is set to be 15%, which equals the depreciation rate used in the BEA estimation of R&D capital.[17] We set the initial value of organization capital stock (OC_{i0}) as the SG&A expenses divided by the growth rate and depreciation rate:

$$OC_{i0} = \frac{SGA_{i,1}}{g + \delta_0}, \tag{2}$$

where g is the growth rate. The growth rate refers to the assumed real growth rate of firm-level SG&A expenditures, which is set to 10% (Eisfeldt & Papanikolaou, 2013).[18] Missing SG&A expenses are set to zero. To enhance the comparability across firms, we scale organization capital by the firm's contemporary book assets. For brevity, we refer to this ratio as organization capital hereafter.

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[15] We obtain quantitatively similar results when we release the restrictions on excluding financial firms and retain firms with December fiscal years.

[16] https://beta.bls.gov/dataQuery/find?fq=survey[cu]&s = popularity:D

[17] We follow Eisfeldt and Papanikolaou (2013) and set the depreciation rate of organization capital at 15% because BEA applied 15% to depreciate R&D capital in 2006 (see their page 1381). To check the robustness of our results, we further test different depreciation rates of organization capital at 10%, 12%, 18% and 20%. All results are qualitatively similar and support our hypothesis that the organization capital effect is much more significant in firms with R&D activities.

[18] We set the real growth rate of SG&A expenses at 10% because Eisfeldt and Papanikolaou (2013) claim that it is the statistics derived from their sample. We have confirmed that the real growth rate of SG&A expenses during their (our) sample period is 13.7% (12.9%), which justifies the usage of the 10% SG&A real growth rate employed in Eisfeldt and Papanikolaou (2013) and our paper. In untabulated tests, the results of setting SG&A growth rate from 2% to 15% are qualitatively similar and support our hypothesis.

Since the level of organization capital varies across firms, we follow Eisfeldt and Papanikolaou (2013) and first group firms using the Fama and French (1997) 17 industry classifications and then sort the firms into five quintiles by their organization capital. Finally, we form five VW portfolios by the industry-relative rank of firms' organization capital and rebalance the portfolios every end of June. The hedge portfolio return is thus constructed by buying Portfolio 5 (firms with highest organization capital) and selling Portfolio 1 (firms with lowest organization capital).

To investigate the role of R&D activity, we introduce two variables, *R&D dummy* and *R&D intensity*. *R&D dummy* is a binary variable that equals one if a firm has positive R&D expenses and zero otherwise. We calculate *R&D intensity* as R&D expenses divided by the market value of equity. Missing R&D expenses are set to zero (Chambers et al., 2002).

2.3 | Summary statistics

Table 1 reports the summary statistics.[19] In Panel A, we report, for each variable, the time-series averages of cross-sectional mean, median, standard deviation and cross-sectional first and third quantiles. Detailed descriptions of variables are presented in the Appendix. The mean organization capital is 1.184 and the median is 0.893. These statistics closely resemble those of Eisfeldt and Papanikolaou (2013). The mean and median of *R&D dummy* are both 0.5, indicating that roughly half of our sample firms lack the R&D information.

Panel B presents the overview of how organization capital differentiates firm characteristics in the five portfolios. Compared with firms with lower organization capital, firms with higher organization capital are on average smaller in size and lower in book-to-market ratio, asset growth, operating profitability and leverage. The differences in variables between portfolio 1 and portfolio 5 are statistically significant, suggesting the need to control for these variables in later regressions. In general, we document a pattern similar to that of the sample firms in Eisfeldt and Papanikolaou (2013). We also find that both *R&D intensity* and *R&D dummy* are positively associated with organization capital. That is, higher organization capital groups have more R&D firms with more R&D-intensive activities.

3 | EMPIRICAL RESULTS

In this section, we test the hypothesis that the hedge portfolio returns formed by organization capital should be higher for firms that conduct R&D activities than for firms that do not engage in R&D investment. We use the Fama and French (2015) five-factor model and a number of robustness checks to explore the role of R&D in alpha associated with organization capital. We also perform Fama and MacBeth (1973) regressions as additional tests to examine our hypothesis.

3.1 | Portfolio sorts: Five-factor model

We start with the re-examination of Eisfeldt and Papanikolaou (2013) by extending the sample period to 2017 and using the Fama and French (2015) five-factor model. Specifically, we carry out the following regression:

$$\left(r_m^p - r_{f,m}\right) = \alpha + \beta \bullet MKT_m + s \bullet SMB_m + h \bullet HML_m + r \bullet RMW_m + c \bullet CMA_m + e_m, \tag{3}$$

[19] We report the summary statistics on portfolios sorted by R&D intensity in Appendix Table A1 and Pearson and Spearman correlations between organization capital, R&D intensity, size, book-to-market ratio, asset growth, momentum, operating profitability, leverage, illiquidity and SA index in Appendix Table A2.

TABLE 1 Summary statistics

Panel A: Summary statistics	Mean	Median	Std	Q1	Q3
Organization capital	1.184	0.893	1.111	0.437	1.523
R&D dummy	0.500	0.500	0.499	0.000	1.000
R&D intensity	0.031	0.002	0.061	0.000	0.036
Size	1446	216	4343	56	829
Book-to-market ratio	0.802	0.658	0.902	0.348	1.084
Asset growth	0.233	0.082	0.574	−0.013	0.245
Momentum (%)	11.738	5.951	44.477	−17.055	31.902
Operating profitability	0.193	0.222	0.577	0.076	0.354
Leverage	0.185	0.141	0.183	0.027	0.288
Illiquidity	3.813	0.297	11.638	0.042	1.925
SA index	−2.754	−2.776	0.777	−3.299	−2.249

Panel B: Portfolio sorts							
Portfolio	**1**	**2**	**3**	**4**	**5**	**5 – 1**	**t-value**
Organization capital	0.293	0.625	0.957	1.394	2.750	2.457	(38.58)
R&D dummy	0.340	0.485	0.546	0.577	0.562	0.222	(17.76)
R&D intensity	0.014	0.023	0.031	0.039	0.050	0.036	(15.98)
Size	1943	1689	1646	1455	523	−1420	(−7.20)
Book-to–market ratio	0.887	0.820	0.814	0.803	0.690	−0.197	(−6.87)
Asset growth	0.406	0.284	0.218	0.151	0.071	−0.335	(−10.72)
Momentum (%)	11.570	12.200	12.740	11.820	10.150	−1.420	(−1.24)
Operating profitability	0.225	0.220	0.202	0.193	0.121	−0.104	(−7.93)
Leverage	0.243	0.211	0.177	0.152	0.139	−0.104	(−21.23)
Illiquidity	2.116	2.331	3.292	4.203	7.648	5.532	(11.37)
SA index	−2.920	−2.880	−2.830	−2.720	−2.410	0.510	(24.51)

Note: This table presents the summary statistics of the sample. Panel A shows the mean, median, standard deviation (*std*), quantile 1 (Q1) and quantile 3 (Q3). Panel B shows the mean of the five portfolios sorted on organization capital. Following Eisfeldt and Papanikolaou (2013), we sort firms into five portfolios based on firms' organization capital relative to their industry peers. We classify firms by the Fama and French (1997) 17 industry classifications. See the Appendix for detailed variable definitions.

where r^p_m is the VW portfolio returns of portfolio p in month m; $r_{f,m}$ is the 1-month treasury bill (T-bill) rate; MKT_m is the CRSP VW index return in excess of 1-month treasury bill rate; SMB_m is the size factor; HML_m is the value premium factor; RMW_m is the profitability factor; CMA_m is the investment factor. e_m denotes the residual (Fama & French, 1993, 2015; Hou et al., 2015).[20]

In Table 2, we report the mean monthly portfolio excess returns in Panel A. To calculate the mean monthly portfolio excess returns, we first subtract the contemporaneous 1-month treasury bill rate from the VW portfolio returns and then take the time-series averages of these values. We present a portfolio alpha based on the Fama and French (2015) five-factor model as well as factor loadings of the five factors in Panel B. Overall, our results closely replicate those

[20] We thank Prof. Kenneth R. French for making these factors publicly available on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Detailed definitions of these pricing factors are presented his website as well.

TABLE 2 Organization capital and stock returns

Portfolio	1	2	3	4	5	5 – 1
Panel A: Mean monthly portfolio excess returns						
E[R]-r_f (%)	6.071 **(2.29)**	6.104 (2.21)	7.309 (3.25)	7.576 (3.24)	9.346 (3.94)	3.274 (2.32)
Panel B: Abnormal returns under the Fama and French (2015) five-factor model						
Alpha (%)	−0.362	−0.572	−0.724	−0.361	1.993	2.356
	(−0.64)	(−0.77)	(−0.84)	(−0.56)	(2.43)	(2.94)
MKT	1.045	1.067	0.992	0.943	0.928	−0.117
	(27.74)	(69.68)	(27.04)	(68.25)	(21.74)	(−1.92)
SMB	−0.059	0.013	−0.004	−0.147	0.093	0.151
	(−1.62)	(0.48)	(−0.07)	(−3.68)	(0.93)	(1.27)
HML	0.071	−0.169	−0.217	−0.138	−0.276	−0.347
	(1.62)	(−3.27)	(−5.98)	(−2.86)	(−3.57)	(−4.07)
RMW	−0.159	−0.110	0.204	0.343	0.199	0.358
	(−3.34)	(−2.40)	(3.36)	(9.14)	(3.43)	(4.27)
CMA	−0.046	0.115	0.376	0.306	0.346	0.392
	(−0.76)	(2.88)	(3.57)	(3.90)	(5.01)	(3.83)
Adj. R^2	0.920	0.917	0.873	0.848	0.815	0.168

Note: This table reports the value-weighted (VW) average monthly excess returns (%t) and factor loadings of the Fama and French (2015) (FF) five-factor model regressions. The five factors are market factor (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (CMA). Firms are sorted into quintiles by organization capital relative to their industry peers. Portfolio 1 (5) indicates the lowest (highest) organization capital quintile. 5 – 1 indicates the hedge portfolio with a long position on the highest organization capital portfolio and a short position on the lowest organization capital portfolio. Panel A presents the mean monthly excess returns as the VW portfolio return over the risk-free rate ($E[R] - r_f$). Panel B presents the results under the Fama and French (2015) five-factor model. We annualize the monthly regression coefficients by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

of Eisfeldt and Papanikolaou (2013).[21] The five portfolios' excess return exhibit a monotonically increasing pattern as the organization capital increases. The annual excess return of the hedge portfolio is 3.27%, which is statistically significant at the 5% level. For the Fama and French (2015) five-factor model, we document an annual alpha of the hedge portfolio as 2.36%, which is consistent with Eisfeldt and Papanikolaou (2013).

To investigate our hypothesis, we group firms into two subsamples: those with R&D expenditures and those without, and repeat the factor model regression in equation (3) for the two subsamples. In Table 3, we report the average portfolio returns over the risk-free rate and the coefficients of the five-factor model of the subsamples and find evidence supporting our hypothesis. The portfolios' returns over the risk-free rate exhibit similar patterns as documented in Table 2. The scale, however, is higher for the subsample with R&D expenses than for the subsample without R&D expenses. The annual hedge portfolio return formed by firms with R&D is 3.42% (significant at the 5% level), while the hedge portfolio return formed by firms without R&D is 2.35% (not significant), indicating that the presence of R&D activities explains 32.7% (32.7% = (3.42 − 2.35)/3.27) of the hedge portfolio return. Controlling for common risk factors, we document an annual alpha of 2.41% for the hedge portfolio returns of the group with R&D activity, and 0.41% for the group without R&D. The former is statistically significant at the 5% level, while the latter is not significant. These results indicate that the positive relationship between alpha and organization capital is more prominent for firms that conduct R&D activities.

[21] We replicate the results of Eisfeldt and Papanikolaou (2013) using the Fama and French (2015) five-factor model in Appendix Table A3, where the sample period starts in 1970 and ends in 2008.

TABLE 3 Organization capital and stock returns—Subsample of research and development (R&D) activity

	Without R&D						With R&D					
Portfolio	1	2	3	4	5	5 – 1	1	2	3	4	5	5 – 1
Panel A: Mean monthly portfolio excess returns												
$E[R]$-r_f (%)	5.776	6.528	6.419	8.496	8.129	2.354	6.584	6.401	7.682	7.608	10.008	3.424
	(2.12)	(2.28)	(2.58)	(3.64)	(2.94)	(1.34)	(2.39)	(2.28)	(3.34)	(3.18)	(3.95)	(2.06)
Panel B: Abnormal returns under the Fama and French (2015) five-factor model												
Alpha (%)	−3.202	−1.975	−3.222	−1.738	−2.792	0.410	1.569	0.369	0.011	0.053	3.981	2.412
	(−2.37)	(−1.55)	(−2.34)	(−1.10)	(−1.84)	(0.32)	(1.68)	(0.59)	(0.01)	(0.08)	(4.29)	(2.53)
MKT	1.122	1.084	0.997	1.004	1.031	−0.091	1.013	1.058	0.988	0.934	0.901	−0.111
	(91.51)	(54.94)	(27.83)	(50.73)	(44.13)	(−3.76)	(20.41)	(62.49)	(24.88)	(58.70)	(20.60)	(−1.73)
SMB	0.117	0.161	0.321	0.175	0.306	0.189	−0.161	−0.003	−0.070	−0.205	0.037	0.198
	(4.32)	(2.75)	(3.24)	(6.35)	(5.03)	(3.33)	(−3.61)	(−0.11)	(−1.36)	(−5.48)	(0.33)	(1.34)
HML	0.045	−0.026	−0.067	0.068	0.003	−0.042	0.066	−0.226	−0.249	−0.174	−0.344	−0.410
	(1.01)	(−0.37)	(−0.71)	(1.29)	(0.15)	(−0.93)	(1.03)	(−4.31)	(−6.41)	(−3.17)	(−3.78)	(−4.33)
RMW	0.171	0.157	0.379	0.498	0.536	0.365	−0.338	−0.215	0.163	0.307	0.060	0.398
	(3.66)	(4.54)	(3.27)	(4.73)	(12.05)	(12.30)	(−4.99)	(−3.66)	(2.48)	(8.64)	(0.97)	(3.59)
CMA	0.122	0.128	0.336	0.296	0.383	0.262	−0.132	0.102	0.379	0.317	0.258	0.390
	(2.80)	(2.90)	(2.74)	(3.48)	(6.88)	(3.71)	(−1.43)	(2.02)	(3.07)	(3.74)	(2.94)	(2.60)
Adj. R^2	0.886	0.842	0.770	0.720	0.768	0.129	0.847	0.874	0.845	0.812	0.759	0.124

Note: This table reports the VW average monthly excess returns (%) and factor loadings of the Fama and French (2015) five-factor model regressions. We classify firms into two subsamples: firms without R&D expenses and firms with R&D expenses. Firms are sorted into quintiles by organization capital relative to their industry peers. Portfolio 1 (5) indicates the lowest (highest) organization capital quintile. 5 – 1 indicates the hedge portfolio with a long position on the highest organization capital portfolio and a short position on the lowest organization capital portfolio. Panel A presents the mean monthly excess returns as the VW portfolio return over the risk-free rate ($E[R] - r_f$). Panel B presents the results under the Fama and French (2015) five-factor model. We annualize the monthly regression coefficients by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

We further discuss potential data snooping biases (Harvey & Liu, 2020) in intevvrpreting the alpha found in this paper. According to Harvey and Liu (2020), threshold values for tests of significance depend on a parameter p_0 (i.e., an assumption for the prior fraction of true strategies or the fraction of managers who have skills). Harvey and Liu (2020) suggest that neither 2.0 (the traditional t-statistic cutoff for 5% significance) nor 3.0 (based on Harvey et al., 2016) is optimal from the perspective of the investor. Noted that p_0 is purely a belief in the prior. We do not know exactly what the value of p_0 would be in the real world. In one case that Harvey and Liu (2020) examine when setting p_0 to 10% and controlling the Type I error rate at 5%, the t-statistic threshold is about 2.4 (see page 22). Given that we find that the annual abnormal return of the hedge portfolio sorted by organization capital is 2.41% with t-statistic equal to 2.53, our result remains significant even when we have adopted a higher t-statistic threshold. However, we acknowledge the possibility that our result could become non-significant when we impose a more restricted p_0 (e.g., 5% or smaller) together with holding the Type I error rate at 5%.

We further propose an extreme portfolio strategy, which buys stocks with the highest organization capital and with R&D activity, and short sells stocks with the lowest organization capital and without R&D activity. This extreme portfolio earns an excess return of 4.23% (significant at the 5% level) and has an annualized alpha of 7.18% (significant at the 5% level), implying that the extreme portfolio offers practitioners an outstanding investment strategy.[22] We also test three additional strategies: (1) buying stocks with the highest organization capital and with R&D activity and short selling stocks with the highest organization capital but without R&D activity, (2) buying stocks with the lowest organization capital and with R&D activity and short selling stocks with the lowest organization capital but without R&D activity, (3) buying stocks with the highest organization capital and without R&D activity and short selling stocks with the lowest organization capital but with R&D activity. These portfolios do not earn alphas as large as the extreme portfolio.[23]

To further support the contention that differences in organization capital explain firms' different average abnormal returns, Eisfeldt and Papanikolaou (2013) also sort firms by their presorting univariate beta of organization capital (OMK-beta).[24] They document significant abnormal return for the long–short portfolio sorted by OMK-betas, which is consistent with the results sorted by organization capital. Therefore, to provide further evidence for our hypothesis, we imitate this approach in Table 4 and demonstrate that sorting firms by presorting univariate beta of organization capital also leads to consistent results.

We first calculate the presorting univariate beta as the coefficient under a simple linear regression of monthly returns on an organization capital factor, rolling for 12 months, where the organization capital factor is the VW hedge portfolio returns defined in Section 2.2. Next, we sort the firms into five quintiles using the presorting univariate beta, and then form five corresponding VW portfolio returns, rebalanced every end of June. The results are reported in Table 4, where we document the alpha of the hedge portfolio formed by the R&D firms as 3.06% (significant at the 5% level) and that formed by the non-R&D firms as 2.42% (not significant). The results suggest that even if we consider high organization capital firms as those having high organization capital sensitivity (i.e., high presorting univariate beta), R&D still plays a role in the abnormal return entailed by organization capital.

3.2 | Robustness checks

We conduct a number of robustness checks using different pricing models, different ways to construct portfolio returns and different sampling methods. In Panel A of Table 5, we present results based on different pricing models,

[22] Results are listed in Appendix Table A4.

[23] We also provide the same specification (i.e., the Fama–French three-factor model and the Carhart four-factor model with both the new data period and original data period of Eisfeldt and Papanikolaou (Eisfeldt & Papanikolaou, 2013) to ensure better comparability and present them in Appendix Tables A5 to A7.

[24] They estimate OMK-beta using weekly data, calculated as the coefficient under a simple linear regression of weekly returns on an organization capital factor. See the appendix of Eisfeldt and Papanikolaou (2013) for more details.

TABLE 4 Organization capital beta and stock returns—Subsample of R&D activity

	Without R&D						With R&D					
Portfolio	1	2	3	4	5	5 – 1	1	2	3	4	5	5 – 1
Panel A: Mean monthly portfolio excess returns												
$E[R]{-}r_f$ (%)	4.888	6.423	6.626	6.442	8.364	3.476	7.549	6.171	7.366	5.589	9.572	2.023
	(1.57)	(2.51)	(2.55)	(2.38)	(3.03)	(1.64)	(2.74)	(2.47)	(2.75)	(2.35)	(3.60)	(1.18)
Panel B: Abnormal returns under the Fama and French (2015) five-factor model												
Alpha (%)	−3.154	−3.990	−2.212	3.599	−0.733	2.420	0.025	−0.457	1.877	−0.098	3.081	3.057
	(−2.44)	(−2.73)	(−1.59)	(−2.76)	(−0.34)	(1.08)	(0.03)	(−0.62)	(3.05)	(−0.09)	(3.01)	(2.41)
MKT	1.003	1.073	1.076	1.148	1.060	0.057	0.958	0.981	0.984	1.004	0.953	−0.005
	(39.74)	(59.51)	(66.07)	(34.62)	(35.93)	(1.68)	(54.50)	(44.04)	(28.96)	(36.02)	(28.29)	(−0.18)
SMB	0.157	0.168	0.140	0.213	0.206	0.049	−0.010	−0.182	−0.133	−0.119	−0.118	−0.108
	(2.39)	(4.00)	(4.10)	(3.99)	(5.86)	(0.75)	(−0.36)	(−4.54)	(−7.28)	(−2.31)	(−3.35)	(−2.10)
HML	0.042	0.133	0.016	−0.083	0.028	−0.014	−0.051	−0.106	−0.166	−0.172	−0.200	−0.149
	(0.45)	(1.77)	(0.19)	(−1.23)	(0.38)	(−0.16)	(−0.83)	(−1.75)	(−4.51)	(−4.06)	(−2.26)	(−2.11)
RMW	0.210	0.452	0.205	0.362	0.243	0.033	0.191	0.018	−0.178	−0.027	0.080	−0.111
	(2.98)	(6.44)	(3.59)	(5.04)	(3.27)	(0.35)	(4.42)	(0.49)	(−5.32)	(−0.92)	(2.10)	(−1.45)
CMA	0.102	0.228	0.198	0.301	0.176	0.074	0.172	0.165	0.085	−0.009	0.240	0.068
	(0.98)	(4.39)	(1.37)	(2.51)	(1.90)	(0.41)	(1.85)	(2.19)	(1.02)	(−0.10)	(2.62)	(0.79)
Adj. R^2	0.734	0.829	0.819	0.781	0.744	−0.004	0.750	0.847	0.829	0.799	0.756	0.008

Note: This table reports the VW average monthly excess returns (%) and factor loadings of the Fama and French (2015) five-factor model regressions using subsamples. We classify firms into two subsamples: firms without R&D expenses and firms with R&D expenses. Firms are sorted into quintiles by the presorting univariate beta of organization capital. Portfolio 1 (5) indicates the lowest (highest) presorting univariate beta quintile. 5 – 1 indicates the hedge portfolio with a long position on the highest presorting univariate beta portfolio and a short position on the lowest presorting univariate beta capital portfolio. The presorting univariate beta is the coefficient under a simple linear regression of monthly returns on an organization capital factor, rolling for 12 months. The organization capital factor is the VW hedge portfolio returns defined in Section 2.2. Panel A presents the mean monthly excess returns as the VW portfolio return over the risk-free rate ($E[R] - r_f$). Panel B presents the results under the Fama and French (2015) five-factor model. We annualize the monthly regression coefficients by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

TABLE 5 Robustness checks of asset pricing models

Portfolio	Without R&D			With R&D		
	1	5	5 – 1	1	5	5 – 1
Panel A: Different factor models						
A1. Fama-French (1993) three-factor model	−2.155	0.499	2.653	−0.230	4.892	5.122
	(−1.87)	(0.37)	(2.01)	(−0.32)	(3.97)	(4.41)
A2. Carhart (1997) four-factor model	−1.972	−0.490	1.482	0.490	3.473	2.983
	(−1.86)	(−0.46)	(1.57)	(0.62)	(3.38)	(3.15)
A3. Fama-French (2015) five-factor model plus market return volatility	−3.231	−2.312	0.919	3.089	8.549	5.460
	(−2.16)	(−1.46)	(0.56)	(1.97)	(5.33)	(2.61)
A4. Hou et al. (2021) q5 model	1.839	0.263	−1.576	2.688	4.711	2.023
	(1.57)	(0.17)	(−1.40)	(3.17)	(4.39)	(2.05)
Panel B: Different ways to construct portfolio returns						
B1. Equal-weighted (EW) returns	−2.222	2.094	4.316	0.413	11.511	11.099
	(−1.50)	(1.32)	(1.80)	(0.39)	(3.96)	(3.90)
B2. Log VW returns	−3.431	−1.664	1.767	−0.662	7.149	7.812
	(−2.52)	(−1.57)	(1.29)	(−0.68)	(3.52)	(3.81)
B3. Conditional Fama–French (2015) five-factor model	−1.262	−1.765	−0.509	1.119	3.141	2.554
	(−0.27)	(−0.90)	(−0.31)	(0.19)	(0.92)	(1.78)
Panel C: Different sampling methods						
C1. Exclude firms with price below $5	−2.392	−1.395	0.997	1.946	4.531	2.585
	(−1.79)	(−1.02)	(0.78)	(1.98)	(4.16)	(2.52)
C2. Small firms	−6.579	−6.339	0.240	−2.059	2.981	5.040
	(−4.18)	(−3.17)	(0.12)	(−1.04)	(1.90)	(2.93)
C3. Large firms	−3.119	−2.354	0.765	1.602	4.156	2.554
	(−2.29)	(−1.58)	(0.58)	(1.72)	(4.56)	(2.63)
C4. Exclude micro-cap firms	−3.149	−2.402	0.748	1.607	4.131	2.523
	(−2.33)	(−1.58)	(0.55)	(1.73)	(4.48)	(2.58)

Note: This table presents a number of robustness checks of average abnormal returns sorted by organization capital and R&D activity. In Panels A through C, we sort data by organization capital into five portfolios and further divide the firms into two subsamples: those with R&D and those without. Portfolios (1 to 5) are constructed upon organization capital relative to their industry peers. In Panel A, we compute VW abnormal returns using four different factor models: (A1) Fama and French (1993) three-factor model; (A2) Carhart (1997) four-factor model; (A3) a six-factor model that adds changes in market return volatility; (A4) Hou et al.'s (2021) q5 model. Panel B reports the results of different ways to construct portfolio returns. In Tests B1 and B2, we construct EW and log VW portfolio returns, respectively, and then compute alphas using the Fama–French (2015) five-factor model. In Test B3, we estimate alphas using the conditional Fama and French (2015) five-factor model, where the conditional variables include the dividend yield, the default spread, the term spread and the 1-month T-bill rate and each factor loading is a linear function of these four conditional variables. In Panel C, we use different sampling methods to examine the organization capital effect based on the Fama–French (2015) five-factor model. In Test C1, we exclude the firms with stock price less than $5. In Test C2, we examine the subsample of small firms, defined as a firm size smaller than the median. In Test C3, we examine the subsample of large firms, defined as a firm size larger than the median. In Test C4, we exclude micro-cap firms, defined as a firm size smaller than that of the 10th percentile of NYSE stocks. For brevity, we present only the alpha for Portfolio 1, Portfolio 5 and the hedge portfolio (5 – 1). We annualize the monthly regression coefficients by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

including the Fama and French (1993) three-factor model (Panel A1), Carhart (1997) four-factor model (Panel A2), Da et al. (2012) six-factor model that adds changes in market return volatility to the Fama–French's (2015) five-factor model (Panel A3) and q5 model of Hou et al. (2021) (Panel A4). Panel B shows results based on different ways to construct portfolio returns. In Panels B1 and B2, we use EW and log VW portfolio returns (Ikenberry & Ramnath, 2002; Loughran & Ritter, 2000), respectively, based on the Fama–French's (2015) five-factor model. In Panel B3, we compute alpha using the conditional Fama and French (2015) five-factor model, where the conditional variables are the dividend yield, the default spread, the term spread and the 1-month T-bill rate, and each factor loading is a linear function of these four conditional variables (Petkova, 2006; Petkova & Zhang, 2005).[25] Panel C reports the tests using different sampling methods. In Panel C1, we exclude the firms with stock price less than $5 (Loughran & Ritter, 1996). In Panels C2 and C3, we examine the subsample of small firms and large firms, respectively, where small firms are those with a firm size smaller or equal to the median, and large firms are those with a firm size larger than the median. Finally, in Panel C4, we exclude micro-cap firms from the sample (Fama & French, 2008).[26]

For brevity, we report only the alpha of Portfolio 1, Portfolio 5 and the hedge portfolio in Table 5. The results show that our main finding in Table 3 holds under different factor models, weighting schemes and sampling methods. The alpha of the hedge portfolio in firms with R&D generally remains statistically significant and is larger than that in firms without R&D. The organization effect in stock returns in general does not exist in firms without R&D.

4 | R&D-RELATED RISK AND FIRM CHARACTERISTICS

Lev and Sougiannis (1996) document a positive intertemporal relationship between R&D and stock returns and further deduce that the association either results from investors' underreaction or reflects the market risks associated with R&D. In general, previous studies attribute the positive relationship between R&D and stock returns to either risk compensation or mispricing. In the risk explanation, firms investing in R&D are riskier in nature and endure more uncertainty than non-R&D firms do. In the dynamic model proposed by Berk et al. (2004), R&D firms are riskier because investment in an R&D project is in essence a compound option. Chambers et al. (2002) demonstrate that the average excess returns' cross-year variation of R&D-intensive firms are more volatile than non-R&D firms and further conclude that the positive relationship is due to the failure to properly control for risk. As argued by D. Li (2011), R&D risks increase with financial constraints because firms raise funds (either internally or externally) to conduct R&D activities. Consequently, financially constrained firms are prone to suspend or discontinue R&D projects. Overall, the risk explanation attributes the positive relationship between R&D and stock returns to R&D firms bearing the systematic risks.

The alternative explanation is mispricing, which is led by firm characteristics and may require years for the market to correct. In this case, mispricing occurs when investors fail to correctly recognize or slowly react to the information content embedded in R&D. L. K. Chan et al. (2001) propose that the investors are misled by the conservative accounting rules for R&D, resulting in abnormal returns related to R&D. Eberhart et al. (2004) suggest that R&D increase is beneficial, while the market is slow to recognize the extent of the benefit, causing an overall under-reaction and the abnormal returns associated with R&D. By documenting a significant abnormal return generated from a long–short strategy taking advantage of firms' past R&D and innovation records, Cohen et al. (2013) further argue that the market tends to consistently misvalue innovation and underreact to the information contained in R&D investments. Collectively, the mispricing explanation contends that abnormal return related to R&D is induced by the misinterpretation of or underreaction to the R&D firms' characteristics.

[25] The dividend yield is the sum of dividends accruing to the CRSP VW market portfolio over the previous 12 months divided by the level of the market index. The default premium is the yield spread between Moody's Baa and Aaa corporate bonds, where we retrieve the default yields from the Federal Reserve Economic Data (FRED), Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org. The term spread is the yield spread between the 10-year and the 1-year treasury bond, where we retrieve the bond yields from CRSP.

[26] We identify firms with market cap below the 10th NYSE percentile as micro-cap firms.

In the previous section, we demonstrated that R&D activity plays an essential role in the abnormal returns associated with organization capital. That is, the hedge portfolio return sorted by organization capital is higher for R&D firms than for non-R&D firms. Hence, we can earn a higher alpha on the hedge portfolio formed by organization capital and implement our investment strategy with R&D information. Thus, we continue to investigate which aspect of the nature of R&D is associated with the driving force of the organization capital effect. We discuss the nature of R&D from two perspectives: systematic risk and firm characteristics.

4.1 | R&D systematic risk

In the spirit of the Fama and French (1993) three-factor model, Al-Horani et al. (2003) construct an R&D factor to capture the R&D systematic risk. They show that the explanatory power of the Fama and French (1993) three-factor model is enhanced when it is augmented with a factor that captures R&D systematic risks. Dedman et al. (2009), Gregory and Michou (2009) and Lin and Wang (2016) adopt a similar approach, in which they control for the R&D systematic risk using R&D-augmented factor models. Therefore, to examine whether the organization capital effect is driven by the systematic risk associated with R&D, we compute alpha using the Fama–French (2015) five-factor model with an R&D factor. That is, we run the following augmented factor model:

$$\left(r_m^p - r_{f,m}\right) = \alpha + \beta \bullet MKT_m + s \bullet SMB_m + h \bullet HML_m + r \bullet RMW_m + c \bullet CMA_m + rd \bullet R\&Dfactor_m + e_m, \tag{4}$$

where $R\&Dfactor_m$ denotes the R&D risk factor in month m, and other settings are the same as equation (3). Should the abnormal return associated with organization capital be driven by the systematic risk of R&D activity, adding the R&D risk factor would draw down both the value and significance of the alpha of the hedge portfolio.

We adopt four specifications for the R&D risk factor, which is the VW hedge portfolio return sorted by R&D information, and we report the alphas of the Fama–French (2015) five-factor model plus the R&D factor in Table 6. In Panel A, we use R&D intensity and sort firms into five quintiles by R&D intensity (R&D-to-size ratio) and then form the VW hedge portfolio return by buying stocks with the highest R&D intensity and selling those with the lowest R&D intensity. In Panel B, we form the VW hedge portfolio return by buying firms conducting R&D activities and selling those not investing in R&D. In Panel C, we construct the VW hedge portfolio return controlling for size effect in the spirit of Fama and French (1993). To be specific, we first sort stocks by market capitalization into small, medium and large, using the 30th and 70th NYSE percentile breakpoints, and then we perform an independent sort on the firm's R&D dummy (i.e., those firms that conduct R&D activity and those that do not). These sorts produce six VW portfolios. The hedge portfolio return is thus the average of the three with-R&D portfolios minus the average of the three without-R&D portfolios. In Panel D, the VW hedge portfolio return is constructed in a manner similar to Panel A, but we sort firms into five quintiles by R&D intensity within the Fama and French (1997) 17 industry classifications.

Table 6 presents the results of the Fama–French (2015) five-factor model augmented with an R&D factor. We find that the alpha of the hedge portfolio remains significant in all panels. For instance, the alpha for the hedge portfolio is 2.03% annually in Panel B, which is statistically significant at the 5% level. That is, taking the systematic risk of R&D into consideration does not explain the alpha associated with organization capital. Firms with high organization capital probably earn abnormal returns for reasons other than systematic risk compensation for R&D activities.[27]

[27] As an additional test, we independently sort firms into 15 (3 × 5) sub-groups according to three R&D intensity groups (i.e., without R&D, below-median and above-median groups) and five organization capital groups and compute the hedge portfolio return sorted by organization capital for each R&D intensity group. The results show significant alphas for the hedge portfolios formed by firms with below-median R&D intensity but weak or non-significant alphas for those of above-median R&D intensity.

TABLE 6 Organization capital and stock returns-using Fama and French (2015) five-factor model with R&D factor

Portfolio	1	5	5 – 1
Panel A: R&D factor constructed upon R&D intensity			
Alpha (%)	−0.381	2.194	2.575
	(−0.67)	(2.71)	(2.98)
R&D factor	0.006	−0.066	−0.072
	(0.41)	(−2.90)	(−2.96)
FF five factors	YES	YES	YES
Adj. R^2	0.919	0.818	0.178
Panel B: R&D factor constructed upon R&D activity			
Alpha (%)	−0.081	1.948	2.029
	(−0.14)	(2.31)	(2.04)
R&D factor	−0.078	0.012	0.091
	(−0.90)	(0.13)	(0.80)
FF five factors	YES	YES	YES
Adj. R2	0.920	0.814	0.169
Panel C: R&D factor constructed controlling for size effect			
Alpha (%)	−0.325	2.373	2.698
	(−0.49)	(2.65)	(2.21)
R&D factor	−0.008	−0.077	−0.069
	(−0.06)	(−1.56)	(−0.62)
FF five factors	YES	YES	YES
Adj. R^2	0.919	0.815	0.168
Panel D: R&D factor constructed upon industry-relative R&D intensity			
Alpha (%)	−0.300	1.994	2.294
	(−0.57)	(2.39)	(2.87)
R&D factor	−0.033	0.000	0.033
	(−1.41)	(−0.01)	(0.84)
FF five factors	YES	YES	YES
Adj. R^2	0.920	0.814	0.168

Note: This table reports the alphas and factor loadings of the Fama and French (2015) five-factor model adding an R&D factor. Firms are sorted into quintiles by organization capital relative to their industry peers. Portfolio 1 (5) indicates the lowest (highest) organization capital quintile. 5 – 1 indicates the hedge portfolio with a long position on the highest organization capital portfolio and a short position on the lowest organization capital portfolio. There are four specifications of *R&D factor*. In Panel A, *R&D factor* is a VW hedge portfolio return formed by buying stocks with the highest R&D intensity (R&D-to-size ratio) quintile and selling those with the lowest R&D intensity quintile. In Panel B, *R&D factor* is a VW hedge portfolio return formed by buying firms conducting R&D activities and selling those not investing in R&D. In Panel C, *R&D factor* is constructed as a VW hedge portfolio return controlling for size effect in the spirit of Fama and French (1993). To be specific, we first sort stocks by market capitalization into small, medium and large, using the 30th and 70th NYSE percentile breakpoints, and then we perform an independent sort on firm's R&D dummy (i.e., those that conduct R&D activity and those that do not). These sorts produce six VW portfolios. The hedge portfolio return is thus the average of the three with-R&D portfolios minus the average of the three without-R&D portfolios. In Panel D, *R&D factor* is constructed in a similar fashion to Panel A, but we sort firms into five quintiles by R&D intensity within Fama and French (1997) 17 industry classifications. For brevity, we present only the results for Portfolio 1, Portfolio 5 and the hedge portfolio (5 – 1). We omit the coefficients of *MKT*, *SMB*, *HML*, *RMW*, and *CMA* and denote them as *FF five factors*. We annualize the monthly regression coefficients by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

4.2 | R&D firm characteristics

Recognizing that the organization capital effect is not driven by R&D systematic risk, we further examine whether the effect is in part due to R&D-related firm characteristics. Kadiyala and Rau (2004) and Cohen and Lou (2012) suggest that investors usually underreact to firm-specific information, such as R&D expenditures, especially when the information is complicated and hard to digest. Moreover, Daniel and Titman (2006) and Jiang (2010) both argue that intangible returns, which are related to the R&D spending of a firm, are likely to indicate firms' growth options. When misvaluation of intangible information drives the alpha, the organization capital effect of stock returns would be stronger for firms with R&D activity.

To explore to what extent the organization capital risk accounts for the organization capital effect, Eisfeldt and Papanikolaou (2013) estimate alphas using a two-factor model including a market factor and an organization capital factor. They show that the alphas for the five portfolios sorted by organization capital are not significant. They interpret the results as indicating that the returns related to organization capital can be attributed to the co-movements between these portfolio returns and the organization capital factor, which is the hedge portfolio return formed by organization capital quintiles. Considering the role of R&D activity, we conduct a similar test to verify their interpretation, in which we add an organization capital factor to the Fama and French (2015) five-factor model. In other words, we consider the following regression using both the pooled sample and the subsamples of R&D groups:

$$\left(r_m^p - r_{f,m}\right) = \alpha + \beta \bullet MKT_m + s \bullet SMB_m + h \bullet HML_m + r \bullet RMW_m + c \bullet CMA_m + oc \bullet OCfactor_m + e_m, \quad (5)$$

where $OCfactor_m$ represents the organization capital factor in month m identical with that defined in Eisfeldt and Papanikolaou (2013). Other variable settings remain the same as those in equation (3).[28]

Table 7 reports the coefficients of the Fama–French (2015) five-factor model augmented with an organization capital factor, as well as the Gibbons et al. (1989) statistic (GRS statistic hereafter). We document findings similar to those of Eisfeldt and Papanikolaou (2013) using the pooled sample, where we find no significant alpha in the five portfolios sorted by organization capital. In the subsamples split by the existence of R&D activity, however, we document significant alphas in half of the 10 portfolios. The significant GRS statistics in both subsamples further support the contention that the alphas of these portfolios are statistically different from zero.[29] Thus, consistent with the spirit of Daniel and Titman (1997), Fama and French (2008), Cooper et al. (2010) and Conrad et al. (2013), this evidence corroborates our contention that the alpha of organization capital is indeed relevant to the R&D-related firm characteristics.

4.3 | Fama and MacBeth regressions

We continue the analysis with Fama and MacBeth (1973) cross-sectional regressions of stock returns. From July of year $t+1$ to June of year $t+2$, we regress monthly raw returns of individual stocks on organization capital of year t and other control variables including size, book-to-market ratio, asset growth and operating profitability in the spirit of the setting of Fama and French (2015) five-factor model. To explore how the organization capital effect interacts with R&D activities, we also examine return predictability of *organization capital with R&D activity* (i.e., $OC \times R\&D\ dummy$) and *organization capital without R&D activity* (i.e., $OC \times (1 - R\&D\ dummy)$).

Table 8 shows the results of Fama and MacBeth (1973) cross-sectional regressions of stock returns with Models 1 to 3 (Models 4 to 6) being estimated by the EW (VW) least square method. In Model 1 of Panel A, we include

[28] Eisfeldt and Papanikolaou (2013) compute the organization capital factor as the long-short portfolio formed by organization capital quintiles, that is, the factor equals the VW portfolio return of the fifth quintile minus the VW portfolio return of the first quintile.

[29] Numerous studies use this method in testing the validity of factor models, such as Fama and French (1993, 1996, 2015), Pástor and Stambaugh (2003) and Ang et al. (2006).

TABLE 7 Organization capital and stock returns-using Fama and French (2015) five-factor model with organization capital factor

	Pooled sample					Without R&D					With R&D				
Portfolio	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Alpha (%)	0.462	−0.246	−1.033	−0.773	0.544	−2.831	−1.685	−3.279	−1.997	−3.522	2.642	0.695	−0.356	−0.352	2.449
	(0.96)	(−0.31)	(−1.12)	(−1.06)	(0.63)	(−2.00)	(−1.31)	(−2.18)	(−1.22)	(−2.56)	(2.77)	(1.04)	(−0.35)	(−0.43)	(2.42)
OC factor	−0.378	−0.149	0.142	0.189	0.665	−0.170	−0.133	0.026	0.119	0.335	−0.493	−0.150	0.169	0.186	0.703
	(−8.37)	(−6.64)	(2.92)	(4.45)	(28.24)	(−4.11)	(−3.83)	(0.25)	(1.14)	(3.51)	(−5.46)	(−4.58)	(3.67)	(3.28)	(18.37)
FF five factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.946	0.920	0.877	0.857	0.910	0.890	0.845	0.769	0.722	0.787	0.889	0.877	0.851	0.820	0.856
GRS	0.54					3.15					2.29				
p(GRS)	0.75					0.01					0.04				

Note: This table reports the alphas and factor loadings of the Fama and French (2015) five-factor plus an organization capital factor. Firms are sorted into quintiles by organization capital relative to their industry peers. Portfolio 1 (5) indicates the lowest (highest) organization capital quintile. *OC factor* denotes the organization capital factor, which is a VW hedge portfolio return formed by a long position on the highest organization capital portfolio and a short position on the lowest organization capital portfolio. We conduct the test using the pooled sample and the subsamples of firms with- and without- R&D. For brevity, we omit the coefficients of *MKT*, *SMB*, *HML*, *RMW* and *CMA* and denote them as *FF five factors*. *GRS* is the *F*-statistic of Gibbons et al. (1989), testing the hypothesis that the regression intercepts for a set of five portfolios are all zero. *p(GRS)* is the *p*-value of *GRS*. We annualize the monthly regression coefficient by multiplying by 12. Newey–West adjusted *t*-statistics are presented in parentheses.

TABLE 8 Fama–MacBeth regression—R&D activity and organization capital effect

Panel A	EW			VW		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.411	1.420	1.277	1.053	1.063	0.725
	(4.39)	(4.42)	(3.11)	(2.10)	(4.26)	(1.42)
Organization capital	0.140			0.108		
	(2.04)			(1.14)		
Organization capital		0.203	0.235		0.114	0.120
with R&D activity		(2.33)	(2.51)		(1.83)	(1.94)
Organization capital		0.051	0.052		0.080	0.095
without R&D activity		(1.20)	(1.36)		(1.25)	(1.51)
Log(size)	−0.084	−0.087	−0.038	−0.029	−0.029	−0.021
	(−1.97)	(−2.03)	(−0.70)	(−0.78)	(−1.01)	(−0.77)
Book-to-market ratio	0.194	0.202	0.213	0.187	0.179	0.173
	(6.35)	(6.54)	(7.40)	(1.18)	(1.50)	(1.70)
Asset growth	−0.332	−0.329	−0.423	−0.365	−0.362	−0.376
	(−2.87)	(−2.89)	(−2.98)	(−3.89)	(−2.14)	(−1.91)
Operating profitability	0.004	0.006	0.008	0.102	0.096	0.085
	(0.12)	(0.20)	(0.40)	(1.11)	(1.01)	(1.07)
Other control variables			Yes			Yes
Adj. R^2	0.020	0.021	0.042	0.083	0.088	0.138
Avg. Obs.	1498	1498	1355	1496	1496	1354

(Continues)

TABLE 8 (Continued)

Panel B	EW			VW		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.411 (4.39)	1.132 (2.87)	0.937 (2.22)	1.053 (2.10)	0.735 (2.05)	0.481(0.83)
Organization capital	0.140 (2.04)			0.108 (1.14)		
Organization capital component related to R&D		0.284 (2.22)	0.325(2.50)		0.253 (2.17)	0.293 (2.99)
Organization capital component unrelated to R&D		0.112 (2.14)	0.126 (2.66)		0.052 (1.31)	0.059 (1.14)
Log(size)	−0.084 (−1.97)	−0.058 (−1.26)	−0.008 (−0.13)	−0.029 (−0.78)	−0.003 (−0.09)	0.012 (0.41)
Book-to-market ratio	0.194 (6.35)	0.220 (6.20)	0.231 (8.00)	0.187 (1.18)	0.241 (1.96)	0.245 (2.36)
Asset growth	−0.332 (−2.87)	−0.327 (−2.53)	−0.420 (−2.70)	−0.365 (−3.89)	−0.353 (−2.02)	−0.368 (−1.85)
Operating profitability	0.004 (0.12)	−0.004 (−0.12)	0.003 (0.16)	0.102 (1.11)	0.081 (0.89)	0.080 (1.04)
Other control variables			Yes			Yes
Adj. R^2	0.020	0.023	0.043	0.083	0.098	0.145
Avg. Obs.	1498	1498	1355	1496	1496	1354

Note: This table reports the coefficient estimations of the Fama–MacBeth (1973) regression analysis. The dependent variable is monthly raw returns (%). *Organization capital* is the ratio of organization capital to book assets. *R&D dummy* is a binary that equals one if the firm has *R&D* and zero otherwise. *Organization capital with R&D activity* is defined as *Organization capital* times *R&D dummy*. *Organization capital without R&D activity* is *Organization capital* times (1 − *R&D dummy*). In Panel B, *Organization capital component related to R&D* and *Organization capital component unrelated to R&D* is defined as the fitted value and the residual, respectively, of the following equation:

$$Organizationcapital_{i,t} = \alpha + \beta_1 \cdot R\&Dintensity_{i,t} + \beta_2 \cdot log(size)_{i,t} + \beta_3 \cdot Book - to - marketratio_{i,t} + \beta_4 \cdot Assetgrowth_{i,t} + \beta_5 \cdot Operatingprofitability_{i,t} + e_{i,t}.$$

Models 1 to 3 are EW least square regression model, whereas Models 4 to 6 are VW least square regression models. In all models, we include *logarithm of size*, *book-to-market ratio*, *asset growth* and *operating profits* as control variables. Models 3 and 6 further include *momentum*, *leverage*, *illiquidity* and *SA index* as control variables. Variable definitions are described in the Appendix. Newey–West adjusted *t*-statistics are presented in parentheses.

organization capital, *size*, *book-to-market ratio*, *asset growth* and *operating profitability* as independent variables in the regression. The effect of organization capital is positive with a coefficient of 0.140 and significant at the 5% level, corroborating the finding in Table 2 that future return is higher when a firm has higher organization capital. Moreover, Model 2 shows that the coefficient on *organization capital with R&D activity* is significant at 0.203, while the coefficient on *organization capital without R&D activity* is not significant and much smaller at 0.051, implying that the organization capital effect is closely related to R&D activities. In Model 3, we further include *momentum*, *leverage*, *illiquidity* and *SA index* as additional control variables, and the results are robust.[30]

Model 4 of Panel A reveals that the organization capital effect is no longer significant when we use the VW least square method, indicating that the organization capital effect may largely be concentrated among small firms. The evidence is consistent with Green et al. (2017), who find that organization capital fails to predict cross-sectional stock returns when they use VW least square method or exclude micro-cap firms in the Fama and MacBeth (1973) regressions (see their tab. 4). In Models 5 and 6, however, the coefficients on *organization capital with R&D activity* are significant at 0.114 and 0.120, respectively, suggesting that R&D activity can be the driving force of the organization capital effect.

For the robustness check, we decompose organization capital by regressing organization capital on R&D intensity, natural log of size, book-to-market ratio, asset growth and operating profitability. The fitted value and residual of the regression are defined as the *OC component related to R&D* and the *OC component unrelated to R&D*, respectively. Panel B of Table 8 presents the results, showing that the *OC component related to R&D* is consistently significant in all regression models and much larger than the *OC component unrelated to R&D* (Models 2, 3, 5 and 6). The return predictability of OC unrelated to R&D, if any, exists only in the EW case (i.e., small firms). Overall, the evidence in Table 8 is in line with Green et al. (2017), suggesting that the organization capital effect is concentrated among small firms and can be driven by firms with R&D activities.[31]

Moreover, Cohen et al. (2013) find a significantly positive coefficient on the interaction term of high R&D dummy and high R&D ability dummy ($ability_{high} \times R\&D_{high}$) in the Fama–MacBeth regressions and argue the existence of return predictability of R&D ability. We test this idea by including $ability_{high} \times R\&D_{high}$ in the regressions. We find that the coefficient of *organization capital* × *R&D dummy* is positive and significant after controlling for $R\&D_{high}$ and $ability_{high} \times R\&D_{high}$.[32] This result suggests that our main finding of the significant organization capital effect in R&D firms is not driven by the R&D ability effect.

Furthermore, engineers and technicians tend to have high labor mobility (Almeida & Kogut, 1999; Saxenian, 1994), for example, the engineers in Silicon Village may have a turnover rate of around 30% or even more. While Eisfeldt and Papanikolaou (2013) suggest that the movement of key employees drives the stock returns of organization capital, the high mobility of R&D people could enlarge the asset pricing effect of organization capital. Upon introducing the idea of the UTSA, which prevents the leakage of non-public knowledge of the focal firm to its competitors through employee movement, we find that R&D activity affects organization capital effect more when engineers could move to other firms easily under weak trade secret law protection. In sum, these results provide further evidence supporting our hypothesis that the organization capital effect is stronger for firms engaging in R&D activities.[33]

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[30] We control these variables following Jegadeesh and Titman (1993), Pástor and Stambaugh (2003) and Hadlock and Pierce (2010). We use Amihud's (2002) illiquidity measure and calculate the constraint index following Hadlock and Pierce's (2010) SA index.

[31] We perform similar tests in factor model regressions. We compute R&D capital based on L. K. Chan et al. (2001) and decompose the organization capital into *component related to R&D* (i.e., R&D capital) and the *component unrelated to R&D*. We then sort firms into quintiles based on the *component related R&D* and *component unrelated to R&D*, separately, and run the five-factor model regressions and report the abnormal returns (i.e., alphas) in Appendix Tables A8. We find that the annual alpha of the hedge portfolio based on the sorting of the *component unrelated to R&D* is only 0.74% ($t = 0.84$), whereas the alpha of the hedge portfolio based on the *component related to R&D* is 5.42% ($t = 3.32$). The overall results are consistent the findings in our Fama and MacBeth (1973) regressions.

[32] The result is presented in Models 1 to 4 of Appendix Table A9. We also find a weak correlation between organization capital and R&D ability, with the correlation coefficient equal to 0.01 only.

[33] To investigate the channel that induces to what extent the high turnover of engineers may affect the organization capital effect for R&D firms, we introduce a binary that equals one if the firm's headquarters are located in a state that has enacted the UTSA and zero otherwise (Glaeser, 2018) in the Fama and Mac-

Thus far, we have demonstrated to what extent the organization capital effect is affected by the R&D activity. Here, we consider the situation from the opposite point of view to see how the organization capital effect impacts the well-documented return predictability of R&D intensity. To execute this examination, we perform the regression analysis using Fama and French (2015) five-factor model and Fama and MacBeth (1973) cross-sectional regressions of stock returns. In Appendix Table A10, upon the Fama and French (2015) five-factor model, we find that the organization capital does not explain the R&D effect because the alpha of the two hedge portfolios is not significant.[34] Appendix Table A11 reports the results of the Fama and MacBeth (1973) cross-sectional regressions, where the non-significant coefficient of the interaction term of R&D intensity and organization capital in Model 2 indicates that the R&D effect cannot be attributed to organization capital.[35] In sum, we find that the return predictability of R&D intensity cannot be explained by the organization capital.

4.4 | Alternative measures

In this paper, we use R&D expenditures to detect R&D activity and to enable comparison with the literature that examines the return predictability of R&D (Al-Horani et al., 2003; Donelson & Resutek, 2012; Eberhart et al., 2004; Gu, 2016; D. Li, 2011; Lin & Wang, 2016).[36] Here, we adopt two alternatives, (1) capitalizing both SG&A and R&D, and (2) using the current year SG&A and R&D expenses, to perform the tests. The results show that the alpha of the hedge portfolio sorted by organization capital is significant only in the R&D subsample and that the magnitude of alpha is larger for the R&D subsample than for the non-R&D subsample.[37] A similar pattern holds when we use the current year t values of both SG&A and R&D. These results are consistent with our main finding in Table 3. Therefore, our conclusion is unchanged under different measures of organization capital and R&D activity.

5 | CONCLUSION

The importance and real impact of intangible assets, including organization capital and R&D, have been extensively explored in the economic and finance literature. While we know much about the return predictability of R&D, we have relatively limited knowledge about the stock returns associated with organization capital as proposed by Eisfeldt and Papanikolaou (2013). Therefore, this paper investigates to what extent the well-known R&D investment effect may account for the newly developed asset pricing effect of organization capital.

We relate organization capital to R&D by arguing that conceptually the key talent, in whom organization capital is embodied, are those employees who plan and execute R&D projects and that a large portion of R&D expenses are payments to these technical professionals and skilled workers. In Compustat, a portion of R&D expenses is recorded in SG&A expenses, which are the building blocks for measuring organization capital. Thus, R&D is related to organization capital empirically as well. Furthermore, whether due to risk-compensation or mispricing, the positive relationship

Beth (1973) regressions. The UTSA, also known as the law for trade secrets, prevents the leakage of non-public knowledge of the focal firm to its competitors, for example, through employee movement. That is, engineers could easily move to other firms in states without UTSA. The result is presented in Model 5 of Appendix Table A9. We document consistent results when we substitute the industry-relative rank of organization capital for organization capital.

[34] R&D intensity is calculated as the ratio of R&D expenses to market value of equity. We first classify the firms that do not invest in R&D, and then sort the remaining firms into four quartiles by their R&D intensity. We thus form five VW portfolio returns accordingly and rebalance the portfolios every June. We further divide the sample into two subsamples by the median of organization capital.

[35] In Model 1, we document that the coefficient of R&D intensity is 1.752 and statistically significant at the 5% level, indicating that there is a positive relationship between R&D and future returns. In Model 2, we further add organization capital and the interaction term of R&D intensity and organization capital as additional variables into the regression to see how organization capital interact with the R&D effect.

[36] Some literature regarding the discussion on R&D and stock returns use R&D capital (e.g., L. K. Chan et al., 2001; Clausen & Hirth, 2016; Heeley et al., 2006; Lev, 2004; Lev & Sougiannis, 1996).

[37] Please refer to Appendix Table A12 for details.

between R&D and future return is well-documented. Therefore, we believe that the organization capital effect can be attributed to R&D activities and further hypothesize that the organization capital effect is more prominent for firms that invest in R&D than for firms that do not.

Using US data from 1970 to 2017, we find supporting evidence for our hypothesis by documenting that the alphas associated with organization capital are higher in firms that conduct R&D activities. Evidence from portfolio sorts, factor models and cross-sectional return regressions all show that effects of organization capital on stock returns are higher for firms conducting R&D activities than those not engaging in R&D investment.

In the Fama and MacBeth (1973) regressions, the results suggest that organization capital can significantly predict cross-sectional stock returns, and this effect is more pronounced for small firms. To explore how the organization capital effect interacts with R&D, we examine the return predictability of *OC with R&D activity* and *OC without R&D activity*. The coefficients on *OC with (without) R&D activity* are significant (not significant) in both EW and VW least square methods, indicating the organization capital effect can be driven by R&D activities.

Moreover, by introducing an R&D risk factor into the factor model, we demonstrate that the organization capital effect is not fully driven by the R&D systematic risk. Instead, we argue that the R&D firm characteristics, at least partially, drive the organization capital effect. In sum, this paper substantially enriches our knowledge of the relationship between intangible capital and stock returns, especially the role of R&D and organization capital.

Beyond the findings of our study, more research is called for to develop a deeper understanding of the OC effect. For example, future research can identify the salaries and compensation paid to R&D managers or technicians and investigate whether R&D related talent plays an important role in the OC effect. Moreover, Eisfeldt and Papanikolaou (2013) and Yildirim and Allen (2021) argue that the OC effect is related to the labor market systematic risk premium. It would be interesting to know whether and how labor mobility interacts with the OC effect. In addition, SG&A expenses include some items that may be irrelevant in accounting for the OC effect. Future studies are encouraged to dig into SG&A expenses and test which detailed expense items drive the OC effect. Finally, we do not find that factor models fully account for our results. While we cannot rule out a risk-based explanation, future research can formally test whether it is indeed the risk premium that drives the OC effect in stock returns.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Compustat and CRSP. Restrictions apply to the availability of these data, which were used under license for this study.

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APPENDIX: VARIABLE DEFINITION

Variable	Definition and description
Organization Capital	We calculate the stock of organization capital (OC_{it}) as $OC_{it} = (1 - \delta_0)\ OC_{it-1} + \frac{SGA_{i,t}}{cpi_t}$, where $SGA_{i,t}$ is the SG&A expenses of firm i in year t, δ_0 is the depreciation rate set as 15%, and cpi_t is the consumer price index. We calculate the initial stock of organization capital (OC_{i0}) as $OC_{i0} = \frac{SGA_{i,1}}{g+\delta_0}$, where g is the real growth rate of firm-level SG&A expenditures set as 10%. OC_{it} is scaled by book assets in year t. See Section 2.2 for details of the construction of organization capital
Size	The market equity of a firm (in million), computed as an annual (calendar) close price multiplied by common shares outstanding from Compustat. If missing, then compute as absolute of price multiplied by shares outstanding from CRSP. Size is measured at the end of year *t*
Log(size)	Natural logarithm of size
Book-to-market ratio	Book-to-market ratio is the book equity value divided by size, where the book equity value is computed as the total assets minus total liabilities minus total preference stocks. Book-to-market ratio is measured at the end of year *t*
R&D dummy	A binary variable that equals one if the firm has positive R&D expenses and zero otherwise. R&D dummy is measured at the end of year *t*
R&D intensity	R&D expenses divided by size. R&D expenses are measured at the end of year *t*
Asset growth	The growth of assets, defined as total assets at year t minus total assets at year $t-1$ divided by total assets at year $t-1$
Momentum	The holding period returns in the past 12 months (%), skipped a month.
Operating profitability	Operating profitability is calculated as sales minus cost of goods sold minus SG&A expenses minus interest and related expenses and then divided by book common equity. Operating profitability is measured at the end of year *t*
Leverage	We define leverage as the long-term debts divided by total assets. We replace missing values with zero. Leverage is measured at the end of year *t*
Illiquidity	The Amihud (2002) illiquidity measure, which is defined as the time-series average of absolute daily returns divided by daily dollar trading volume from July in year t to June in year $t+1$. Dollar trading volume is calculated as the share trading volume multiplied by the closing price.
SA index	For each year t, financial constraint is calculated as $SA\ index = (-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$, where *Size* is the logarithm of book assets, $Size^2$ is the square of size and *Age* is the number of years the firm has been covered in Compustat with a non-missing stock price