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Misvaluing Effective Investors in Intangible Capital

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Misvaluing Effective Investors in Intangible Capital

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Abstract

Cohen et al. (2013) measure a firm's ability at investing in knowledge capital, a type of intangible capital, through a model that captures how well a firm translates R&D intensity into future sales growth. Using this model, they show that an investment portfolio comprised of firms that have high R&D spending ability and high R&D intensity earn significant positive abnormal returns. I modify their model to capture a broader investment in intangible capital by replacing R&D intensity with SG&A intensity and substituting sales growth with gross profit growth. My measure of ability at investing in intangible capital has two main advantages over Cohen et al.'s (2013) measure. The first advantage is that it can be applied to a larger sample of firms. This is because current US accounting standards give firms discretion over how they report their R&D spending – a proxy for investments in knowledge capital – so many firms do not report this expense separately from SG&A despite evidence of intangible capital creation. The second advantage of my model is that it considers the simple fact that investments can result in revenue generation and/or cost savings, both of which are valuable to a firm. Cohen et al.'s (2013) measure depends on sales growth, so it does not consider firms that are successful at converting intangible capital investments into cost savings. In performing a calendar-time portfolio analysis using my SG&A spending ability measure, I find strong evidence that, on average, firms that have a track record at effectively investing in intangible capital (demonstrate a high ability while also investing heavily in this area) experience positive abnormal returns. Namely, an equal-weighted long portfolio strategy that invests in firms that score in the top quintile of effectiveness has four- and five-factor alphas (using the factors suggested by Carhart 1997 and Fama and French 2016) of 68 ($t = 4.023$, $p < 0.001$) and 68 basis points per month ($t = 3.868$, $p < 0.001$), respectively, which both translate to annual abnormal returns of roughly 8.5%. I also construct a version of my ability measure that depends on sales growth, instead of gross profit growth and find that this specification is not a strong predictor of abnormal returns. Lastly, I perform two additional calendar-time portfolio analyses, sorting firms into portfolios by R&D intensity and Cohen et al.'s (2013) original measure of R&D spending ability as well as a modified ability measure that depends on gross profit growth. I find that I am unable to replicate Cohen et al.'s (2013) findings using an updated sample. Additionally, I find that portfolios sorted on an R&D spending ability measure that depends on gross profit growth produce abnormal returns. However, because these portfolios have a small number of stocks these abnormal returns could be due to firm-specific idiosyncratic shocks.

Github data and code repository is available at https://github.com/dustin-lind/Senior-Thesis

Contents

1 Introduction

In an efficient market, stock prices fully incorporate the value of a firm's intangible assets. Thus, investments in intangible capital should not be associated with future abnormal stock returns. However, there is a growing body of literature, which I summarize below, that highlights the market's inability to properly value firms' investments in intangible capital. In this paper, I build on this literature by modifying Cohen et al.'s (2013) model for measuring a firm's R&D spending ability. R&D is widely recognized as a proxy for the amount that a firm spends on a type of intangible capital known as knowledge capital. Cohen et al.'s (2013) ability measure captures how well a firm's past R&D spending intensity translates into future sales growth. After sorting firms into portfolios based on their R&D spending ability and R&D spending relative to sales ("R&D intensity"), Cohen et al. (2013) perform a calendar-time portfolio analysis. Their results indicate that over their 1980 to 2009 sample period, firms that have a high R&D spending ability estimate and a high R&D intensity earn significant positive abnormal returns. Namely, an equal- and value-weighted portfolio of firms that have high R&D spending ability and high R&D intensity earn four-factor alphas (using the factors suggested by Carhart 1997) of 90 (t = 3.11) and 78 basis points per month (t = 2.27), respectively. This translates to annual abnormal returns of 11% and 9.8%.

Cohen et al.'s (2013) model for measuring R&D spending ability suffers from two major shortcomings. First, their model is designed such that to compute an ability score for a firm in their sample, they must omit those that do not report R&D spending despite evidence of intangible capital creation. Previous literature (see Koh and Reeb 2015) find that a substantial number of firms don't report R&D spending despite filing patents. For this reason, I develop a broader measure of ability at investing in intangible capital based on SG&A spending, which is recognized in economic literature as a proxy for the total amount that a firm invests in intangible capital. Also, SG&A is an expense that virtually every firm reports. I find that of the 21,000+ firms with common stocks listed on the NYSE, AMEX, and NASDAQ over the past 40 years, almost 90% report SG&A spending in a given year. Only 54% of these firms report R&D spending. I demonstrate that my new measure based on SG&A spending can be applied to a larger sample of firms than was possible in Cohen et al.'s (2013) study. This availability of data allows me to increase my sample size and minimize the risk of filtering my sample on industry-specific accounting standards. The second shortcoming of Cohen et al.'s (2013) ability measure is that it does not capture intangible capital investments that result in cost savings. Their measure of ability is based on how successful a firm is at converting intangible capital investments into future sales growth. But cost savings ultimately affect the present value of a firm's future cash flows, and thus should be considered in a measure of ability. I account for this by constructing my ability measure to reflect how SG&A spending intensity translates into future gross profit growth, instead of future sales growth.

Using this modified measure of ability at investing in intangible capital (also referred to in this paper as "SG&A spending ability"), I estimate whether firms that have a high ability at investing in intangible capital and invest heavily in this area experience significant positive abnormal stock returns. I follow Cohen et al.'s (2013) approach for sorting firms into portfolios, but I classify firms into portfolios based on my SG&A spending ability measure and a firm's SG&A intensity instead of R&D spending ability and R&D intensity. I place my most effective investors (high ability and high intensity) in the "GoodSG&A" portfolio and ineffective investors (low ability and high intensity) in the "BadSG&A" portfolio. I also create a hedge portfolio that takes a long position in the GoodSG&A portfolio and a short position in the BadSG&A portfolio.

To identify whether investors correctly value firms that are effective at investing in intangible capital, I perform a calendar-time portfolio analysis using 40 years of past monthly stock data on each of my portfolios. I calculate four-factor alphas (Carhart 1997), and five-factor alphas (Fama and French 2016) for each of the portfolios to determine their abnormal returns. I find that the GoodSG&A portfolio earns significant positive abnormal returns when using the multifactor models: the equal-weighted GoodSG&A portfolio has a Carhart four-factor and Fama/French five-factor alpha of 68 (t = 4.023, p < 0.001) and 68 basis points per month (t = 3.868, p < 0.001), respectively, which both translate to annual abnormal returns of roughly 8.5%. Meanwhile, the value-weighted GoodSG&A portfolio have four- and five-factor alphas of 24 (t = 1.428, p = 0.154) and 20 basis points per month (t = 1.176, p = 0.241), respectively, indicating that investors more accurately price the larger firms than the smaller firms in this portfolio. Nevertheless, these results still indicate that, on average, a firm that demonstrates high effectiveness at investing in intangible capital will experience statistically significant positive abnormal returns. In contrast, the BadSG&A portfolio does not experience strong significant abnormal returns. The equal-weighted BadSG&A portfolio have four- and five-factor alphas of 29 (t = 1.975 p = 0.049) and 26 basis points per month (t = 1.696, p = 0.091). Likewise, the value-weighted BadSG&A portfolio have four- and five-factor alphas of 1 (t = 0.076, p = 0.940) and -18 basis points per month (t = -1.063, p = 0.289). These results indicate that the larger firms seem to experience lower risk-adjusted returns than the smaller firms in the BadSG&A portfolio. Lastly, the equal- and value-weighted hedge portfolios have five-factor alphas of 41 basis points per month (t = 2.180, p = 0.030) and 39 basis points per month (t = 1.641, p = 0.102), respectively.

Additionally, I try to replicate the findings of Cohen et al.'s (2013) study using updated data, as it was the inspiration for my empirical approach. Using monthly stock data from July 1980 to June 2020, I ran a calendar-time portfolio analysis employing their original measure for firm-level R&D spending ability and R&D spending intensity. I also ran another portfolio analysis using a model for R&D spending ability that depends on gross profit growth instead of sales growth, to account for potential cost savings that result from R&D activity. Using updated data, sorting firms into portfolios based on Cohen et al.'s (2013) original measure for R&D spending ability and spending intensity, and calculating Carhart four-factor alphas (as done in Cohen et al. 2013), I find little indication that firms in the equal- and value-weighted BadR&D and GoodR&D portfolios earn abnormal returns. Essentially, I am unable to replicate the findings of Cohen et al.'s (2013) paper using updated data. When I sort firms using my measure for R&D spending ability that depends on gross profit growth, I find that firms in the equal- and value-weighted GoodR&D portfolios have both large and significant abnormal returns. The equal-weighted GoodR&D portfolio has four- and five-factor alphas of 133 (t = 3.327, p < 0.001) and 122 basis points per month (t = 2.983, p = 0.003), respectively. Additionally, my value-weighted GoodR&D portfolio has four and five-factor alphas of 79 (t = 1.990, p = 0.047) and 82 basis points per month (t = 2.068, p = 0.039). Using the five-factor alphas, these translate to annual returns of 15.7% and 10.3%, respectively. However, I find that the number of stocks in this GoodR&D portfolio is well below the 30-stock minimum (as suggested by Statman 1987) to be considered a well-diversified portfolio. Thus, it's unclear if the abnormal returns experienced by these portfolios are due to firm-specific idiosyncratic shocks or the variables that I used for the sorts (i.e., R&D spending ability and R&D intensity).

The rest of my paper proceeds as follows. Section 2 discusses the related literature. Section 3 explains the data and my measure for SG&A spending ability. Section 4 describes the empirical approach that I use in my analysis. Section 5 presents the results. Section 6 presents additional results. Finally, Section 7 summarizes my findings and its implications.

2 Literature Review

This paper extends previous research on the impact of firms' investments in intangible capital (also known as "intangible assets") on firm value. According to Generally Accepted Accounting Principles (GAAP), firms cannot capitalize investments in intangible assets on their balance sheet. Instead, all investments in intangibles must be expensed in the current year –usually under sales, general and administrative (SG&A) or in separate subcategories such as research and development (R&D) and advertising. Eisfeldt et al. (2021) observe how intangible assets are largely absent from traditional measures of firm value despite their growing importance in firms' capital stocks. Multiple studies, including those conducted by Eisfeldt and Papanikolaou (2013b), Falato et al. (2013), Belo et al. (2019), and Ewens et al. (2020) estimate that intangible capital on average comprises approximately half of firm value, with variation from this mean depending on industry factors, such as the labor skill-level and consumer product orientation. Belo et al. (2021) find that the two primary categories of intangible capital, knowledge capital and brand capital, account for 20-43% and 6-25% of firm value, respectively. All else equal, the estimated firm-value decomposition is largely explained by how costly it is to adjust inputs to changing economic conditions, with more valuable types of capital being those with higher adjustment costs. Additionally, with GAAP not requiring the value of intangible assets to be reported on firms' financial statements, several researchers, including Chan et al. (2001) and Eisfeldt et al. (2021) have underscored how these rules complicate the process of equity valuation.

Many researchers including Chan et al. (2001), Eberhart et al. (2004), Joshi and Hanssens (2004), Daniel and Titman (2006), Cohen et al. (2013), and Oh et al. (2016) have investigated whether investors fail to correctly value firms' investments in intangible assets. A consistent failure to correctly value investments in intangible capital should result in abnormal equity returns, which are the unexpected returns from a company's stock after controlling for well-studied risk factors. Under the efficient market hypothesis, stock prices always fully reflect information about the risk and underlying value of intangible assets. Thus, there is no room for investors to make abnormal returns by investing in firms who invest heavily in intangible capital. However, several studies (mentioned below) show that stock prices consistently and predictably misvalue the impact of investments in intangible assets on firm value. Joshi and Hanssens (2004) find a positive and long run impact of advertising spending on market capitalization, and Chan et al. (2001) and Oh et al. (2016) find that firms' investments in brand capital are persistently undervalued by investors: advertising expenditures consistently lead to positive abnormal returns. Chan et al. (2001) find that firms in the highest advertising spending quintile have an average abnormal return of 3.1% per year. Oh et al. (2016) replicate the findings of Chan et al. (2001) using updated data and find that the abnormal annual returns can be as much as 9% in industries where brand capital is relatively more important, such as consumer goods and consumer services.

There are also several studies (mentioned below) that have found that investors consistently misvalue firms' investments in intangible capital through R&D, otherwise known as knowledge capital. Daniel and Titman (2006) argue that investors overvalue the impact of investments in knowledge capital on firm value. However, some evidence indicate that investors underestimate the firm value generated from R&D activity. For example, Chan et al. (2001) find that firms that have high R&D expenditures relative to equity value tend to significantly outperform firms with a low intensity: these firms have a 6.12% average annual abnormal return over the following three years. Meanwhile Eberhart et al. (2004) find that large, unexpected increases in R&D expenditures predict significant positive abnormal stock returns.

Most previous research study the relationship between abnormal returns and the intensity of investments in intangible assets. Meanwhile, little research examines the relationship between firm ability at generating intangible capital and abnormal stock returns. Ability at intangible capital creation can be defined as a firm's effectiveness at converting intangible capital investments into something that the firm values. This is an important area of research because many investments in intangible assets fail to generate any value because of factors such as mistiming, poor forecasting, or budget constraints. Thus, some firms that invest equally in intangible capital can have quite divergent results. Multiple studies, including Chan et al. (2001) and Cohen et al. (2013), find that the raw excess returns of firms that invest heavily in R&D are not significantly different than firms that invest little to none in R&D. Accounting for firms' ability to make successful intangible capital investments along with how much they spend on such investments could possibly reveal new and undetected patterns on investors' misvaluation of the impact of firms' investments in intangible assets. The research that has tried to address this concern has been focused on R&D spending rather than advertising spending or SG&A spending more broadly. This is due to the appeal that R&D spending can be used as a measure of companies' innovation efforts. Hirschleifer et al. (2010) find that firm-level innovative efficiency, measured as patents or citations scaled by research and development expenditures, is a strong positive predictor of future returns after controlling for firm characteristics and risks.

My approach to measuring firm-level ability at investing in intangible capital most closely relates to that of Cohen et al. (2013), who develop another simple, yet very compelling method to compute firms' ability to generate intangible assets through R&D spending by looking at which firms do best at translating R&D intensity into future sales growth. In addition to designing a rigorous empirical approach, Cohen et al. (2013) use a more detectable output measure compared to patents, because many firms who successfully invest in knowledge capital never file for patents. Also, the value of patents, which are not reported by firms, vary substantially. Arundel and Kabla (1998) estimate that less than 40% of firms file patents for their technological breakthroughs. Using past financial and stock return data, Cohen et al. (2013) find an equal- and value-weighted portfolio of firms that have high R&D spending ability and high R&D intensity earn four-factor alphas of 90 (t = 3.11) and 78 basis points per month (t = 2.27), respectively. This translates to annual abnormal returns of 11% and 9.8%.

My research differs from Cohen et al. (2013) and others for two reasons. First, instead of limiting my focus to R&D expenditures, I use SG&A expenditures to construct my ability measure and to track intangible capital investment intensity. Koh and Reeb (2015) find that a substantial number of publicly traded firms in the US fail to separately provide any information regarding their corporate R&D efforts, despite evidence that these firms still invest in projects that generate knowledge capital. These same researchers also note that there exist different industry standards for reporting R&D expenditures because GAAP rules leave considerable discretion among firm managers as to what can be classified as an R&D expense.[1] Eisfeldt et al. (2021) argue that using 100% of SG&A instead of relying on separately reported R&D, advertising, and other non-production related expenses is the most reliable way to track intangible capital formation.

[1] In Compustat, R&D and advertising expenses are included in SG&A expense as XSGA.

The second way that my research differs from previous studies is that my ability measure is meant to capture how intangible capital investments convert into future gross profit growth, instead of future sales growth as in Cohen et al.'s (2013) study or patent and citation counts as in Hirshleifer et al.'s (2010) paper. As previously mentioned, most firms fail to file patents even for successful investments in intangible assets, so using patents as an outcome variable could undercount the number of firms that have a high ability at converting investments into financial success. Meanwhile using sales growth as an outcome variable assumes that investments in intangible capital are purely revenue-generating. However, intangible capital investments could also result in cost-savings. For example, a company could spend money on a new piece of software that reduces the costs associated with selling its products. By using sales growth as the dependent variable to calculate firm ability, Cohen et al. (2013) may have failed to account for the firms who achieved cost savings from their investments in intangible assets. Cohen et al. (2013) may have also overcounted the number of firms that generated additional revenue from their intangible capital investments but failed to generate any significant value because their investments resulted in an increase in the costs of selling their products or services. By using gross profit growth as an outcome variable when determining ability at investing in intangible capital, I account for the fact that investments in intangible capital can be revenue-generating as well as cost saving, both of which are equally valuable to a company.

3 Data and Summary Statistics

I obtain data on monthly stock returns, share prices, shares outstanding, and miscellaneous security information (i.e., exchange codes, share codes, etc.) from the Center for Research in Security Prices (CRSP) and firm-specific accounting data such as gross profits, selling and general administrative (SG&A) expenses, etc., from Compustat over a period from January 1962 to

December 2020.[2] As in previous stock market anomalies research, such as that conducted by Cohen et al. (2013) and Oh et al. (2016), my sample includes all NYSE, AMEX, and NASDAQ common stocks (CRSP exchange codes 1-3 and share codes 10-12). Because of their unique characteristics, I exclude real estate investment trusts, close-ended funds, and non-US firms that trade in the United States (CRRP share codes >12). Additionally, my sample only includes common stocks with valid (i.e., non-missing) SG&A intensity and SG&A spending ability estimates, which I define below, for each year. The SG&A variable from Compustat (i.e., labeled with the mnemonic xsga) includes *all* non-direct business costs, such as advertising and R&D expenses, even when broken out separately from SG&A in a firm's accounting records.[3] As mentioned above, researchers argue (see Eisfeldt et al. 2021) that using 100% of SG&A instead of calculating total intangible capital investments by summing R&D, advertising, and other non-production related expenses is the most reliable way to track intangible capital investments.

Table 1 shows that, over my July 1980 to June 2020 sample period, I analyze a larger sample than used by Cohen et al. (2013), whose sample only includes a subset of firms that voluntarily report R&D separately from SG&A. Koh and Reeb (2015) find that a substantial number of firms fail to report R&D spending, despite evidence of innovation activity. In my sample of 21,000+ firms with common stocks on the NYSE, AMEX, and NASDAQ (which I label as "CRSP Universe"), only 54% of them report R&D spending. Meanwhile, over 89% of these

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[2] I initially draw on a larger sample size than used in my portfolio analysis to allow for a sufficient back window to compute my SG&A spending ability measure.

[3] For more information on what other non-direct business costs are included under xsga, visit Compustat's Fundamentals Annual data dictionary at https://wrds-www.wharton.upenn.edu/pages/get-data/center-research-security-prices-crsp/annual-update/crspcompustat-merged/fundamentals-annual/.

firms report SG&A spending. My sample is smaller than the CRSP Universe because, as mentioned above, I only analyze firms that have valid SG&A intensity and SG&A spending ability estimates in a given year. Despite a substantial number of firms reporting SG&A spending, 11% of firms in the CRSP Universe never report a valid SG&A expenditure (or fail to consistently report the expenditure) so they are excluded from my sample. Additionally, many stocks in the CRSP Universe do not have enough past data to calculate a valid estimate for SG&A spending ability. As described below, to calculate SG&A spending ability I use eight years of past data but require at least 75% of SG&A intensity values to be non-missing for each firm-level regression. Given this constraint, I essentially need a stock to have at least six years of past, valid data in my July 1980 to June 2020 sample period to generate its annual SG&A spending ability score. Many companies are in my sample period for less than the required time to generate a valid SG&A spending ability estimate, either because they are delisted from the NYSE, AMEX, and NASDAQ or they are listed near the end of my sample period.

Table 1: Sample comparison

	My Sample	Cohen et al. (2013) Sample	CRSP Universe
# of observations	99,920	45,105	213,434
# of distinct stocks	9,555	4,319	21,538

This table reports the number of observations (i.e., annual fundamental data for a given firm) and the number of distinct stocks across the different samples considered in my analysis (i.e., unique CRSP permno codes). The CRSP Universe is simply a collection of all annual fundamental data for common stocks on the NYSE, AMEX, and NASDAQ from my July 1980 to June 2020 sample period. “My Sample” is a subset of the CRSP Universe sample with valid (i.e., non-missing) SG&A intensity and SG&A spending ability estimates for a given observation. “Cohen et al. (2013) Sample” is a subset of the CRSP Universe sample with valid R&D intensity and R&D spending ability estimates for a given observation.

My measure of ability at investing in intangible capital is based on the same framework as Cohen et al. (2013). Namely, my ability measure is meant to capture simply how good a firm is at converting investments in intangible capital into something it values. However, while Cohen et al.'s (2013) measure for R&D spending ability captures how successful a firm is at converting R&D spending intensity into future sales growth, my ability measure captures how a firm's SG&A intensity translates into future gross profit growth. As mentioned above, the benefits of my measure compared to Cohen et al.'s (2013) is that it (1) can be applied to a larger sample because virtually all firms report SG&A spending and (2) recognizes that cost savings resulting from intangible capital investments are valuable to a firm.

In constructing my model for SG&A spending ability, one concern that I consider is the time horizon used to match SG&A intensity to future gross profit growth. When examining the translated effects of advertising spending on future stock returns, Oh et al. (2016) use a 12-month lag. Meanwhile, Chan et al. (2001) and Eberhart et al. (2004) use a three-year lag when analyzing the effect of R&D spending on future stock returns. There is no general consensus on the time horizon. Thus, I design my measure of SG&A spending ability to account for potential time horizon differences. I use up to a five-year lag in measuring the impact of SG&A intensity on future gross profit growth.

I compute a company's SG&A spending ability for a given year by running rolling firm-by-firm regressions of firm-level gross profit growth (defined as log(GP_t / GP_{t-1})) on the log of lagged SG&A intensity (defined as log(1 + $SG\&A_{t-j}$ / $Sales_{t-j}$), where j = 1, 2, 3, 4, 5). I run separate regressions for five different lags of SG&A (i.e., SG&A from years t – 1, t – 2, t – 3, t – 4, and t – 5); I then take the average of the five regression coefficients on SG&A intensity (defined as γ_j) as my measure of SG&A spending ability. Equations 1 and 2 exhibit how my ability measure is calculated.

$$\log\left(\frac{GP_{i\mid t}}{GP_{i\mid t-1}}\right) = \gamma_0 + \gamma_j \log\left(1 + SG\&A_{i\mid t-j}/Sales_{i\mid t-j}\right) + \epsilon_{i\mid t},\ j = 1,2,3,4,5 \tag{1}$$

$$\text{SG\&A Spending Ability} = \frac{\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 + \gamma_5}{5} \tag{2}$$

Cohen et al. (2013) examine a variety of different model specifications for calculating R&D spending ability, such as running a single regression for each firm's sales growth on the average of the past five years of R&D intensity and using this single coefficient as a measure of ability. However, they find a specification like the one displayed in equations 1 and 2 to work just as well as these other specifications, so they use it as their main model.

To estimate each firm's SG&A spending ability, for every firm in each year I use eight years of past data for every firm-level regression. I then run these regressions on a rolling basis each year using the prior eight years of data. I require a minimum of 75% non-missing SG&A intensity observations and that over half the SG&A intensity observations are positive for each firm-level regression; otherwise, I set the slope coefficients to missing values. Table 2 presents full-sample summary statistics of my SG&A spending ability measure. The average ability estimate is 0.704 while the median is 0.413, indicating that the distribution of ability estimates is positively skewed. Additionally, the average future gross profit growth among companies in my sample is 5.20% and on average SG&A expenditures comprise 23.8% of sales.

Table 2: Summary statistics of ability, SG&A intensity, and gross profit growth

Variable	Mean	Median	Std. Dev.
SG&A Spending Ability	.700	0.409	7.73
$\log(1+SG\&A_{t-j}/Sales_{t-j})$	.238	0.208	.197
$\log(GP_t/GP_{t-1})$	.056	0.068	.382

This table reports pooled summary statistics for SG&A spending ability, SG&A intensity, and gross profit growth for stocks in "My Sample" (see Table 2's description for more information on how "My Sample" is determined). SG&A spending ability is calculated for each firm in a given year by running separate time series regressions using five different lags of SG&A. I then take the simple average of the five different regression coefficients of SG&A intensity to calculate my ability measure:

$$\log\left(\frac{GP_{i\,|\,t}}{GP_{i\,|\,t-1}}\right) = \gamma_0 + \gamma_j \log\left(1 + \ SG\&A_{i\,|\,t-j}/Sales_{i\,|\,t-j}\right) + \epsilon_{i\,|\,t},\ \ j\ =\ 1,2,3,4,5$$

$$\text{SG\&A Spending Ability}\ =\ \frac{\gamma_1\ +\ \gamma_2\ +\ \gamma_3\ +\ \gamma_4\ +\ \gamma_5}{5}$$

A back window of 6-8 years of non-missing data is required to compute a regression coefficient for SG&A spending ability.

4 Empirical Approach

In this section, I introduce my empirical approach for identifying whether investors misvalue firms that are effective at investing in intangible capital. I define effectiveness using a firm's SG&A spending ability estimate and its SG&A intensity: a firm with high SG&A spending ability and high SG&A intensity is considered effective at investing in intangible capital. Conversely, a firm who scores low in SG&A spending ability but spends a relatively large amount on SG&A would not be considered effective. Again, a consistent failure by investors to correctly value these firms that take advantage of their high ability should reveal itself through abnormal equity returns. This is because under the efficient market hypothesis, there is no room for investors to make abnormal returns if all available information about a firm is priced into its stock. As highlighted by Fama and French (2008), there are two approaches that are commonly used to identify anomalies. The first, is to perform a calendar-time portfolio analysis, sorting on anomaly variables (in my case, SG&A intensity and the SG&A spending ability measure that I feature in my analysis), and regressing portfolio returns on well-studied risk factors to estimate its alphas. The second method is to employ monthly Fama and MacBeth (1973) cross-sectional regressions of average returns on anomaly variables. In this paper, I will be using the first approach given its wide popularity in anomaly research and its recognized advantages: it gives a simple picture of how average returns vary across the spectrum of sorts on anomaly variables.

I form portfolios through double sorts using the methodology of Fama and French (2016) and Cohen et al. (2013). The portfolios only contain stocks with positive SG&A intensity and non-missing ability estimates. First, a firm is sorted into one of three portfolios based on its SG&A intensity.

- $SG\&A_{High}$ Portfolio: Stocks in the top 30^{th} percentile of SG&A intensity
- $SG\&A_{Low}$ Portfolio: Stocks in the bottom 30^{th} percentile of SG&A intensity
- $SG\&A_{Mid}$ Portfolio: Stocks that are in neither the portfolios are defined above

Next, a firm is sorted into another one of three portfolios based on its SG&A spending ability score, as described above.

- $Ability_{High}$ Portfolio: Stocks in the top 20^{th} percentile of SG&A spending ability
- $Ability_{Low}$ Portfolio: Stocks in the bottom 20^{th} percentile of SG&A spending ability

Finally, stocks are then sorted into quintiles from the intersection of the SG&A intensity and ability sorts described above, giving me six portfolios. The SG&A intensity and SG&A spending ability estimates used to form the portfolios are from the fiscal year ending in calendar year t – 1 from July to December and calendar year t – 2 from January to June (as in Fama and French 2016 and Cohen et al. 2013).

To examine the relationship between SG&A spending ability, SG&A intensity, and abnormal returns, I analyze three portfolios. The first portfolio takes a long position in the stocks that are in the intersection of the $SG\&A_{High}$ and $Ability_{High}$ sub-portfolios, which I label as the "GoodSG&A" portfolio. In other words, these are firms that exhibit high ability at investing in intangible capital in the past and invest a large amount in this area. The second portfolio takes a long position in the portfolio that is the intersection of the $SG\&A_{High}$ and $Ability_{Low}$ sub-portfolios, which I label as the “BadSG&A” portfolio. This portfolio comprises firms that exhibit a low ability at investing in intangible capital in the past, yet still invest a large amount in this area. The third portfolio is a hedged portfolio that takes a long position in the GoodSG&A portfolio and a short position in the BadSG&A portfolio, which I label as the “Spread” portfolio.

It is possible that any abnormal returns earned by each of the portfolios described above reflect risk differentials contained in the variables that I sorted on to construct the portfolios. To check for this possibility, I compute the four- and five-factor alphas (as in Carhart 1997 and Fama and French 2016) for each of my three portfolios, by running two time series regressions. To compute the four-factor alphas, I run time series regressions of excess portfolio returns on the market (MKT), Size (SMB), Value (HML), and Momentum (UMD) factor returns, as displayed in equation 3. Likewise, to compute the five-factor alphas, I run time series regressions of excess portfolio returns on the market (MKT), Size (SMB), Value (HML), Profitability (RMW), and Investment (CMA) factor returns, as displayed in equation 4. Table 3 defines the key variables and describes the data sources.

$$R_t - R_{Ft} = \alpha + b(R_{Mt} - R_{Ft}) + s\mathrm{SMB}_t + h\mathrm{HML}_t + uUMD_t + e_t \tag{3}$$

$$R_t - R_{Ft} = \alpha + b(R_{Mt} - R_{Ft}) + s\mathrm{SMB}_t + h\mathrm{HML}_t + r\mathrm{RMW}_t + c\mathrm{CMA}_t + e_t \tag{4}$$

Table 3: Variable definitions of five-factor factor model

Variable	Definition	Data Sources
$\boldsymbol{R_t}$	Monthly portfolio raw return	CRSP
$\boldsymbol{R_{Ft}}$	Risk free return	Kenneth French’s Data library
$\boldsymbol{R_{Mt}}$	The return on the value-weighted portfolio of NYSE-AMEX-NASDAQ stocks	Kenneth French’s Data library
$\boldsymbol{SMB_t}$	SMB (Small Minus Big) is the return on a diversified portfolio of small stocks minus	Kenneth French’s Data library

	the return on a diversified portfolio of big stocks	
HML_t	HML (High Minus Low) is the difference between the returns on diversified portfolios of high and low Book/Market stocks	Kenneth French's Data library
RMW_t	RMW (Robust Minus Weak) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability	Kenneth French's Data library
CMA_t	CMA (Conservative Minus Aggressive) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms	Kenneth French's Data library
UMD_t	UMD (Up Minus Down) is the difference between the returns on diversified portfolios with high prior returns and low prior returns	Kenneth French's Data library

5 Results

Panels A and B of Table 4 report alphas for the equal-weighted and value-weighted yearly portfolio sorts, respectively. There is strong indication that, on average, stocks that exhibit a high ability at investing in intangible capital and spend heavily in this area (which I include in the GoodSG&A portfolio) experience positive and significant abnormal monthly returns. Panel A of Table 4 shows that the equal-weighted GoodSG&A portfolio has four- and five-factor alphas of 68 (t = 4.023, p < 0.001) and 68 basis points per month (t = 3.868, p < 0.001), which both translate to annual abnormal returns of roughly 8.5%. Meanwhile, Panel B indicates that the value-weighted GoodSG&A portfolio has four- and five-factor alphas of 24 (t = 1.428, p = 0.154) and 20 basis points (t = 1.176, p = 0.241), which translates to annual abnormal returns of 2.9% and 2.4%, respectively. The difference in results between the equal- and value-weighted portfolios shows that large cap stocks experience lower abnormal returns than small cap stocks in the GoodSG&A portfolio. This is likely because large stocks get more attention from investors and are better priced to reflect all publicly available information about these companies' effectiveness at investing in intangible capital. Nonetheless, it is still clear from the alphas of the equal-weighted GoodSG&A portfolio that, on average, companies that are highly effective at investing in intangible capital experience positive and significant abnormal returns.

While there is strong indication that firms in the GoodSG&A portfolio on average experience positive abnormal returns, there is low indication that stocks that exhibit low ability at investing in intangible capital yet spend heavily in this area (which I include in the BadSG&A portfolio) experience abnormal monthly returns. The four- and five-factor alphas for the equal- and value-weighted portfolios not only vary between positive and negative depending on how they are weighted, but both types of portfolios are also not statistically significant.

Because of the high alphas for the equal-weighted GoodSG&A portfolio, the four- and five-factor alpha for the equal-weighted long-short portfolio (which I label "Spread" and is the difference in returns between the GoodSG&A and BadSG&A portfolios) are also positive and statistically significant (at the 5% significance level). Table 4 shows that the four- and five-factor alphas of the equal-weighted long-short portfolio are 38 (t = 2.067, p = 0.040) and 41 basis points per month (t = 2.180, p = 0.030).

Table 4: Monthly abnormal returns for portfolios

	BadSG&A (Low Ability x $SG\&A_{high}$)	GoodSG&A (High Ability x $SG\&A_{high}$)	Spread (GoodSG&A – BadSG&A)
Panel A: Equal-weighted portfolios			
4-factor α	0.0029	0.0068	0.0038
t-stat	1.975	4.023	2.067
5-factor α	0.0026	0.0068	0.0041
t-stat	1.696	3.868	2.180
Panel B: Value-weighted portfolios			
4-factor α	0.0001	0.0024	0.0023
t-stat	0.076	1.428	0.993
5-factor α	-0.0018	0.0020	0.0039
t-stat	-1.063	1.176	1.641

This table reports monthly portfolio returns for double sorts on SG&A spending ability and SG&A intensity. The SG&A spending ability estimate used to form the portfolios is the ability estimate from the fiscal year ending in calendar year t – 1 from July to December and calendar year t – 2 from January to June. The value-weight portfolios are weighted by the firms' market capitalization at the end of June in fiscal year t – 1 (the month before the portfolios are reconstructed). The weight is held constant through the entirety of the one-year holding period. Four-factor alphas are calculated by taking the intercept coefficient (α) from the following time series regression (as in Carhart 1997):

$$R_t - R_{Ft} = \alpha + b(R_{Mt} - R_{Ft}) + s\mathrm{SM}B_t + h\mathrm{HM}L_t + uUMD_t + e_t$$

Five-factor alphas are calculated by taking the intercept coefficient (α) from the following time series regression (as in Fama and French 2016):

$$R_t - R_{Ft} = \alpha + b(R_{Mt} - R_{Ft}) + s\mathrm{SM}B_t + h\mathrm{HM}L_t + r\mathrm{RM}W_t + c\mathrm{CM}A_t + e_t$$

The sample period is July 1980 to June 2020.

Table 5 presents additional characteristics of the portfolios based on the five-factor model (as in Fama and French 2016). The five-factor loadings in Table 5 suggest that the GoodSG&A and BadSG&A portfolios both have positive loadings on size and negative loadings on profitability, while the BadSG&A portfolio has an additional negative loading on value. These results indicate that the GoodSG&A portfolio favors small, unprofitable stocks, while the BadSG&A portfolio favors small, unprofitable stocks with high book-to-market ratios. Both portfolios have a coefficient of roughly 1 on the market factor indicating that their volatility mirrors the overall market. Meanwhile, the Spread portfolio only has a negative loading on profitability, indicating that stocks in this portfolio are typically unprofitable.

Table 5: Equal-weighted portfolios' five-factor loadings

	BadSG&A (Low Ability x SG&A$_{high}$)	GoodSG&A (High Ability x SG&A$_{high}$)	Spread (GoodSG&A – BadSG&A)
b	1.000	1.001	0.001
$t(b)$	26.79	23.62	0.028
s	0.737	0.850	0.112
$t(s)$	13.25	13.45	1.634
h	0.143	0.001	-0.142
$t(h)$	2.154	0.017	-1.726
r	-0.302	-0.482	-0.180
$t(r)$	-4.289	-6.032	-2.070
c	-0.005	-0.075	-0.070
$t(c)$	-0.046	-0.624	-0.536
R^2	0.756	0.744	0.051

This table presents the five-factor loadings for the equal-weighted portfolios. The factor loadings are the regression coefficients of the Fama-French five-factor model:

$$R_t - R_{Ft} = \alpha + b(R_{Mt} - R_{Ft}) + s\mathrm{SM}B_t + h\mathrm{HM}L_t + r\mathrm{RM}W_t + c\mathrm{CM}A_t + e_t$$

See Table 3 for a description of the different factors in the model (i.e., SMB, HML, etc.)

Tables 6 and 7 display the top eight longest-held company stocks in the BadSG&A and GoodSG&A portfolios, respectively, and the GICS designated sub-industry for each company. Based on these tables, there seems to be some evidence of persistence in firm-level SG&A spending ability, with some companies remaining in either of the portfolios for over 10+ years.

Table 6: Longest holding Stocks in BadSG&A portfolio

Company Name	Number of Years in BadSG&A Portfolio	Sub-Industry
MILLIPORE CORP	14	Life Sciences Tools & Services
WILEY (JOHN) & SONS -CL A	14	Publishing
FORRESTER RESEARCH INC	13	Research & Consulting Services
HAVERTY FURNITURE	13	Home furnishing Retail
MEDTRONIC PLC	12	Health Care Equipment
FLUKE CORP	11	Electronic Equipment & Instruments
PALL CORP	11	Industrial Machinery
AVON PRODUCTS	10	Personal Products

This table reports the top eight longest held stocks in the BadSG&A portfolio. To calculate the number of years held, I look at the BadSG&A portfolio construction over my July 1980 to June 2020 sample period, group the stocks in the sample by their corresponding CRSP permno code, and count the number of observations. The sub-industry of each firm corresponds to the sub-industry code ascribed by the Global Industry Classification Standard (GICS).

Table 7: Longest holding stocks in GoodSG&A portfolio

Company Name	Number of Years in GoodSG&A Portfolio	Sub-Industry
LAWSON PRODUCTS	12	Trading Companies & Distributors
PFIZER INC	11	Pharmaceuticals
US CELLULAR CORP	9	Wireless Telecommunication Services
BIO-RAD LABORATORIES INC	8	Life Sciences Tools & Services
BRISTOL-MYERS SQUIBB CO	8	Pharmaceuticals
URBAN ONE INC	8	Broadcasting
CCUR HOLDING INC	7	Specialized Finance
EBAY INC	7	Internet & Direct Marketing Retail

This table reports the top eight longest held stocks in the GoodSG&A portfolio. See the description of Table 6 to see how the number of years held and the sub-industry are found.

Tables 8 and 9 show the most common industry groups for the companies in the BadSG&A and GoodSG&A portfolios, respectively. Interestingly, we see that the five most common industry groups are the same (yet in different rank order) for both the BadSG&A and GoodSG&A portfolios. The most common industry groups are unsurprisingly those that one would associate with high spending on research and development activities (Technology Hardware & Equipment, Health Care Equipment & Services, Software & Services) as well as advertising and marketing activities (Retailing, Banks).

Table 8: Most common industry groups in BadSG&A portfolio

Industry Group	Number of Companies by Industry Group Over Sample Period (Not Distinct)
Technology Hardware & Equipment	358
Banks	286
Retailing	262
Health Care Equipment & Services	256
Software & Services	233

This table reports the five most common industry groups (as ascribed by GICS) of the stocks in the BadSG&A portfolio over my sample period. To calculate the number of companies by industry group, I look at the BadSG&A portfolio construction over my sample period, group stocks in my sample by their GICS designated industry group code, and count the number of observations.

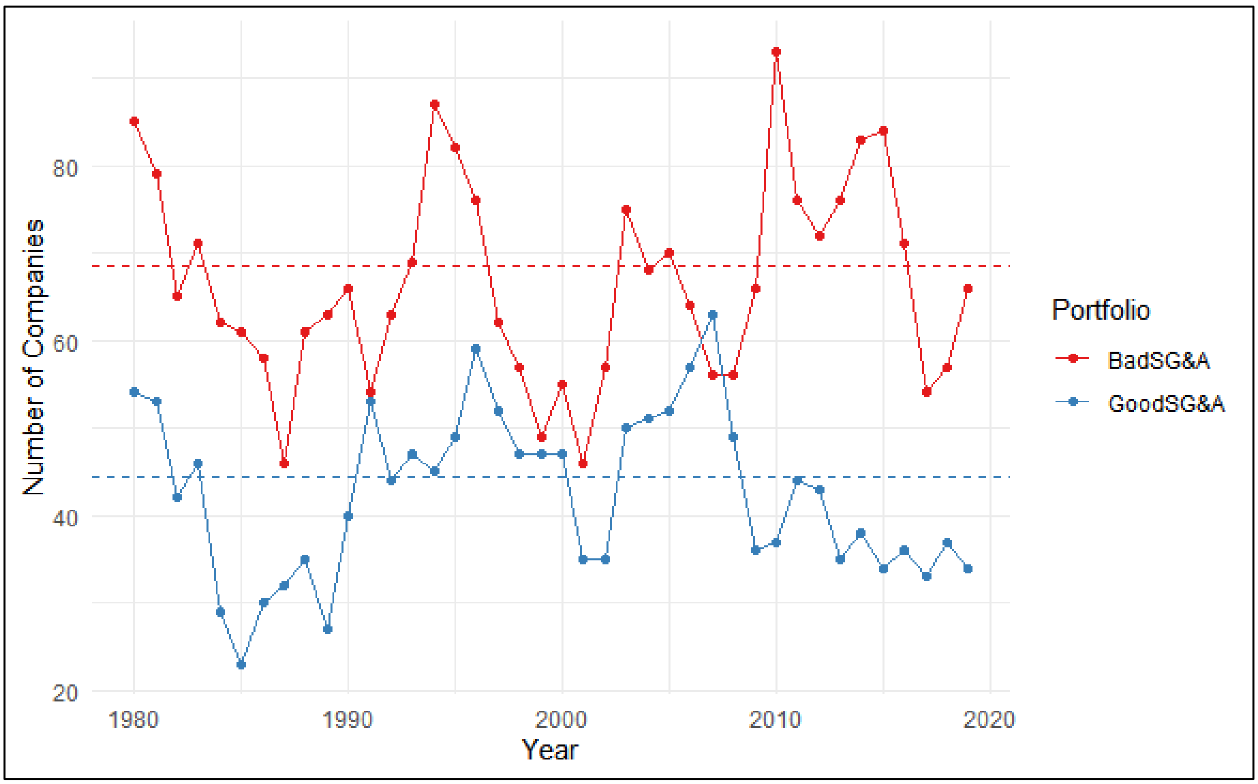
Table 9: Most common industry groups in GoodSG&A portfolio

Industry Group	Number of Companies by Industry Group Over Sample Period (Not Distinct)
Technology Hardware & Equipment	255
Software & Services	197
Health Care Equipment & Services	147
Retailing	133
Banks	115

This table reports the five most common industry groups of the stocks in the GoodSG&A portfolio over my sample period. See Table 8's description to understand how to find the most common industry groups.

Figure 1 displays how the number of stocks in the GoodSG&A and BadSG&A portfolios vary across time. The number of stocks in each of the portfolios is influenced by the distribution of firms sorted on the intersection of their SG&A spending ability and SG&A intensity estimates. Figure 1 shows that on average the number of stocks in the BadSG&A portfolio over my sample period is higher than the number of stocks in the GoodSG&A portfolio (68 vs. 45). This indicates that the distribution of firms based on the intersection of their SG&A spending ability and intensity estimates is right skewed. Consequently, the returns of the GoodSG&A portfolio are slightly more sensitive to the returns of individual stocks relative to the BadSG&A portfolio.

Figure 1: Size of BadSG&A and GoodSG&A portfolios over time



This figure presents a time series of the number of companies in the BadSG&A and GoodSG&A portfolios as well as the average number of companies in each of the portfolios over my July 1980 to June 2020 sample period.

6 Additional findings

For robustness, I construct another measure of SG&A spending ability by analyzing how a firm's SG&A intensity translates into future sales growth, instead of future gross profit growth. I find that the abnormal returns of the GoodSG&A portfolio constructed using this other measure of SG&A spending ability are weaker in magnitude and significance than the GoodSG&A

portfolio constructed using future gross profit growth as the dependent variable in the model for SG&A spending ability.

The alphas of these portfolios are reported in Panels A and B of Table 10. The four- and five-factor alphas for the equal-weighted GoodSG&A portfolio constructed using an ability measure based on sales growth are 38 (t = 2.640, p = 0.009) and 34 (t = 2.209, p = 0.028) basis points, respectively, versus 68 (t = 4.023, p < 0.001) and 68 basis points per month (t = 3.868, p < 0.001) for the equal-weighted GoodSG&A portfolio constructed using an ability measure based on gross profit growth. Unlike the alphas for the equal-weighted BadSG&A portfolio using my original measure for SG&A spending ability, the alphas of the equal-weighted BadSG&A alphas using a measure based on future sales growth are also positive and statistically significant. The four- and five-factor alphas for the equal-weighted BadSG&A portfolio constructed using an ability measure based on sales growth are 35 (t = 2.751, p = 0.007) and 28 (t = 2.040, p = 0.042) basis points, respectively, versus for the equal-weighted GoodSG&A portfolio constructed using an ability measure based on gross profit growth. Given that both the BadSG&A and GoodSG&A portfolios generate significant positive abnormal returns under this approach indicates that an SG&A spending ability measure based on sales growth does a poor job at predicting abnormal returns.

Table 10: Monthly abnormal returns for portfolios (defining ability based on future sales growth)

	BadSG&A (Low Ability x SG&A$_{high}$)	GoodSG&A (High Ability x SG&A$_{high}$)	Spread (GoodSG&A – BadSG&A)
Panel A: Equal-weighted portfolios			
4-factor α	0.0035	0.0038	0.0003
t-stat	2.751	2.640	0.186
5-factor α	0.0028	0.0034	0.0006
t-stat	2.040	2.209	0.360
Panel B: Value-weighted portfolios			
4-factor α	0.0015	0.0023	0.0007
t-stat	1.031	1.319	0.334
5-factor α	-0.0008	0.0018	0.0026
t-stat	-0.531	1.010	1.177

This table reports annual portfolio returns for double sorts on SG&A spending ability (defining ability on how well SG&A spending intensity translates into future sales growth) and SG&A intensity. See Table 4's description to see how four- and five-factor alphas are calculated for each of the portfolios.

Given that I designed my empirical approach to closely mimic that of Cohen et al.'s (2013), which finds that investors consistently undervalue firms that are effective R&D spenders, I also see if Cohen et al.'s (2013) results still hold today using an updated sample size (July 1980 to June 2020) and sorting firms into portfolios based on their original R&D spending ability measure. I also do another analysis using an updated sample size, but sort firms into portfolios based on an R&D spending ability measure that depends on gross profit growth instead. I do this to determine if R&D spending effectiveness is perhaps a better predictor of abnormal monthly returns than SG&A spending effectiveness and to determine if an ability measure that depends on gross profit growth instead of sales growth significantly influences the results. In addition to computing the abnormal returns using Carhart four-factor alphas (as done in Cohen et al. 2013), I also compute Fama/French five-factor alphas (as in Fama and French 2016), to determine if Cohen et al.'s (2013) results may have been influenced by the factor model that they used.

Panels A and B of Table 11 report monthly alphas for the equal-weighted and value-weighted yearly portfolio sorts using R&D intensity and R&D spending ability that depends on sales growth (as defined by Cohen et al. 2013). Based on these results, I find little indication that firms in the BadR&D and GoodR&D portfolios formed under these portfolio sorts experience significant abnormal returns. Both the equal- and value-weighted GoodR&D portfolios do not have statistically significant alphas (at the 5% significance level). The equal-weighted BadR&D portfolio has a five-factor alpha of 58 basis points (t = 2.179, p = 0.030), which is statistically significant, but it does not have a statistically significant 4-factor alpha. Thus, this not a strong indication that this portfolio experiences abnormal returns. Given that Cohen et al.'s (2013) original paper found significant four-factor alphas for the equal- and value-weighted GoodR&D and Spread portfolios using their 1980 to 2009 sample size, my results indicate that these researcher's findings no longer hold today.

Table 11: Monthly abnormal returns for R&D portfolios (defining ability based on future sales growth)

	BadR&D (Low Ability x R&D$_{high}$)	GoodR&D (High Ability x R&D$_{high}$)	Spread (GoodR&D – BadR&D)
Panel A: Equal-weighted portfolios			
4-factor α	0.0049	0.0059	0.0009
t-stat	1.879	1.552	0.220
5-factor α	0.0058	0.0061	0.0003
t-stat	2.179	1.599	0.077
Panel B: Value-weighted portfolios			
4-factor α	0.0002	0.0013	0.0011
t-stat	0.062	0.324	0.227
5-factor α	0.0014	0.0020	0.0057
t-stat	0.436	0.470	0.110

This table reports monthly portfolio returns for double sorts on R&D spending ability (defining ability on how well R&D spending intensity translates into future sales growth) and R&D intensity. See Table 4's description to see how four- and five-factor alphas are calculated for each of the portfolios.

Panels A and B of Table 12 report monthly alphas for the equal- and equity-weighted yearly portfolio sorts using R&D intensity (as defined by Cohen et al. 2013) and an R&D spending ability measure that depends on gross profit growth. The four- and five-factor alphas for the equal- and value-weighted GoodR&D portfolio are both positive and statistically significant. The four- and five-factor alphas for the equal-weighted GoodR&D portfolio are 133 (t = 3.327, p < 0.001) and 122 basis points per month (t = 2.983, p = 0.003). Meanwhile, the four- and five-factor alphas for the value-weighted GoodR&D portfolio are 79 (t = 1.990, p = 0.048) and 82 basis points per month (t = 2.068, p = 0.040). Using the monthly five-factor alphas, this translates to 15.7% and 10.3% of abnormal annual returns for the equal- and value-weighted GoodR&D portfolio, respectively. Given that the alphas of the equal-weighted GoodR&D portfolio are higher than the alphas of the value-weighted portfolio suggest that the largest companies in the GoodR&D portfolio experience lower abnormal returns than the smallest companies. I find little indication that the BadR&D portfolio experience abnormal monthly returns. The four- and five-factor alphas for the BadR&D equal- and value-weighted portfolios are not statistically significant.

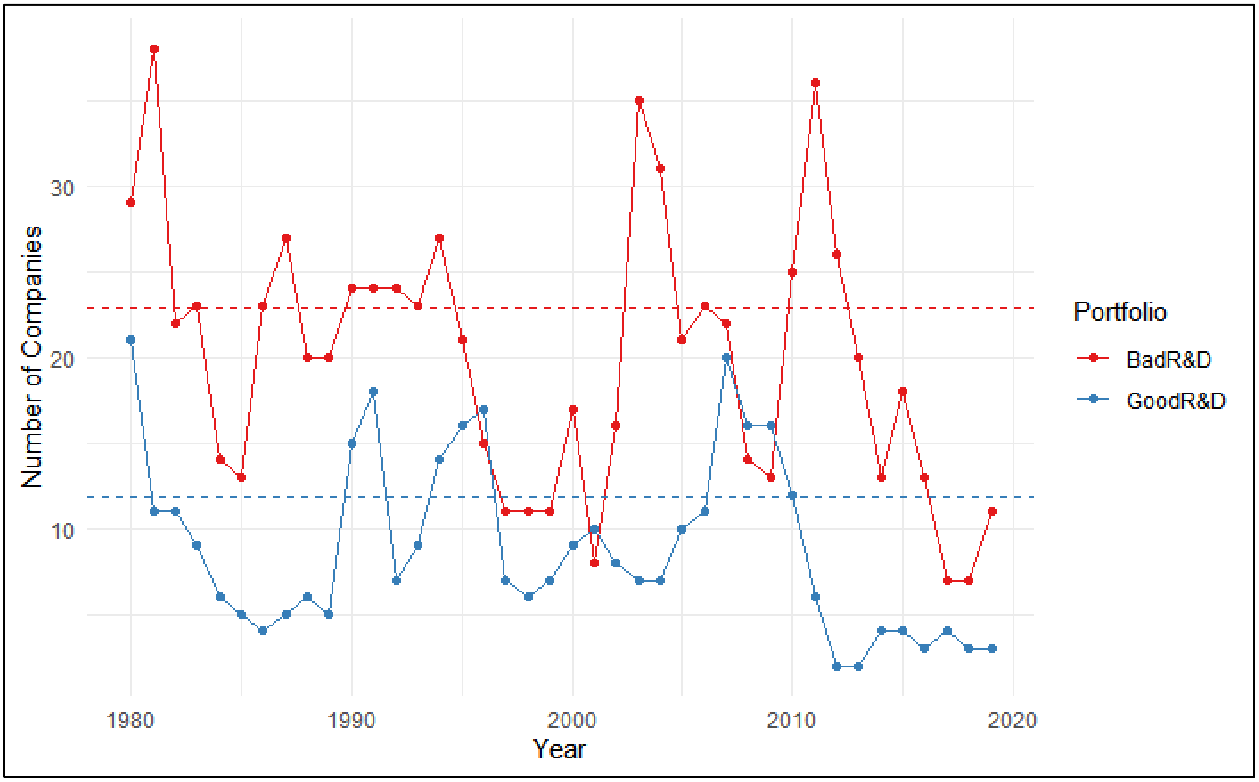
Table 12: Monthly abnormal returns for portfolios (defining ability on R&D spending intensity)

	BadR&D (Low Ability x $R\&D_{high}$)	GoodR&D (High Ability x $R\&D_{high}$)	Spread (GoodR&D – BadR&D)
Panel A: Equal-weighted portfolios			
4-factor α	0.0031	0.0133	0.0102
t-stat	1.079	3.327	2.330
5-factor α	0.0044	0.0122	0.0075
t-stat	1.517	2.983	1.732
Panel B: Value-weighted portfolios			
4-factor α	0.0007	0.0079	0.0073
t-stat	0.198	1.990	1.454
5-factor α	0.0024	0.0082	0.0075
t-stat	0.721	2.068	1.525

This table reports monthly portfolio returns for double sorts on R&D spending ability (defining ability on how well R&D spending intensity translates into future gross profit growth) and R&D intensity. See Table 4's description to see how four- and five-factor alphas are calculated for each of the portfolios.

While the alphas of the GoodR&D portfolio are higher than the alphas of the GoodSG&A portfolio (when they are equal-weighted), they are less statistically significant. Additionally, Figure 2 shows that the number of firms in the GoodR&D portfolio are also significantly lower than the number of firms in the GoodSG&A portfolio (as reported in Figure 1). The average number of stocks in the GoodR&D portfolio during my sample period is 12, which is far below the 30 minimum that Statman (1987) shows will create a well-diversified portfolio. Meanwhile, the average number of stocks in the GoodSG&A portfolio is 45, which is well above 30. Thus, it's unclear if the abnormal returns experienced by the GoodR&D portfolio are due to firm-specific risks or the variables that I used to sort stocks into portfolios (i.e., R&D spending ability and R&D intensity). For this reason, I'm unable to conclude that R&D spending effectiveness is perhaps a better predictor of abnormal monthly returns than SG&A spending effectiveness, with both ability measures based on gross profit growth.

Figure 2: Size of BadR&D and GoodR&D portfolios over time



This figure presents a time series of the number of companies in the BadR&D and GoodR&D portfolios as well as the average number of companies in each of the portfolios over my July 1980 to June 2020 sample period.

7 Conclusion

In this paper, I find that the market appears to consistently undervalue firms that are highly effective at investing in intangible capital. Namely, using a sample of all NYSE, AMEX, and NASDAQ common stocks from July 1980 to June 2020, I find that firms that demonstrate a high ability at investing in intangible capital and spend heavily in this area (which I define as effective investing) experience significant positive abnormal returns after adjusting for well-studied risk factors. This paper also proposes a novel method of measuring a firm's ability at investing in intangible capital, which can be applied to a larger sample of stocks than in previous market anomaly studies and accounts for possible cost savings resulting from past intangible capital investments. Cohen et al. (2013) define ability based on how intangible capital investments translate into future sales growth, even though operating cost savings are a source of value for a firm.

In employing this new measure of ability, an equal-weighted long portfolio strategy that invests in firms that score in the top quintile of effectiveness earns abnormal returns of roughly 8.5% annually. Additionally, I seek to replicate the findings of Cohen et al.'s (2013) study using updated data. Using monthly stock data from July 1980 to June 2020 (the same as my sample range), I ran a calendar-time portfolio analysis employing their original measure for firm-level R&D spending ability and R&D intensity. I also ran another portfolio analysis using a model for R&D spending ability that depends on gross profit growth instead of sales growth, to account for potential cost savings that result from R&D activity. Using updated data, sorting firms into portfolios based on Cohen et al.'s (2013) original measure for R&D spending ability and R&D intensity, and calculating Carhart four-factor alphas (as done in Cohen et al. 2013), I find little indication that firms in the equal- and value-weighted BadR&D and GoodR&D portfolios earn abnormal returns. Essentially, I am unable to replicate the findings of Cohen et al.'s (2013) paper using updated data. When I sort firms using my measure for R&D spending ability that depends on gross profit growth, I find that firms in the equal- and value-weighted GoodR&D portfolios have both large and significant abnormal returns. However, I find that the number of stocks in the GoodR&D portfolio is well below the minimum to be considered a well-diversified portfolio. Thus, it's unclear if the abnormal returns experienced by this portfolio are due to firm-specific risks or the variables that I used for the sorts (i.e., R&D spending ability and R&D intensity).

The results that I present in this paper serve as evidence against the efficient market hypothesis, which states that share prices reflect all information about a stock and that consistent generation of abnormal returns is impossible. I demonstrate that I can build a portfolio based on two measures (i.e., SG&A intensity and SG&A spending ability), which can be easily computed using publicly available data, and generate consistent, significant abnormal returns over a sample period of 40 years. My findings are reason for equity analysts and fund managers to consider a firm's effectiveness at investing in intangible capital when setting price targets and making investment decisions.

My empirical approach can be extended in a few ways to improve the robustness of my findings. First, would be to employ monthly Fama/MacBeth (1973) cross-sectional regressions to further assess the predictive power of my measure for ability at investing in intangible capital. It is recommended that any Fama/Macbeth cross sectional regressions follow the approach of Cohen et al. (2013) and Hirshleifer et al. (2010) by controlling for well-known determinants of stock returns like size, book-to-market, industry classification, etc. Second, would be to do two additional calendar-time portfolio analyses sorting simply on SG&A intensity and separately on SG&A spending ability. Cohen et al. (2013) did this as a robustness check in their paper but found that the portfolios sorted simply on R&D spending ability and separately on R&D intensity did not experience significant abnormal returns. However, my results from Table 10 indicate that sorting simply on SG&A intensity may be a stronger predictor of abnormal stock returns than my SG&A spending ability measure. Third, would be to alter my method for measuring intangible capital investment ability to accommodate firms that have been recently (i.e., less than six years) publicly listed. My method requires a firm to have at least six years of publicly available data on its SG&A spending and gross profits to calculate an ability estimate. Because I'm unable to calculate ability estimates for recently listed firms, this prevents me from including them in my portfolios.

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