Two Persistent Trees: Advertising and the Cross Section of Equity Returns

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How does a firm's advertising policy affect its risk, and its expected return? I propose that the relative size of advertising to capital expenditures is a key statistic that summarizes firms' exposures to their investment opportunities. I find firms that invest more in advertising earn about 4.37% more risk-adjusted returns per year compared to their capital expenditure-intensive counterparts. I then provide a theoretical explanation with a production-based asset pricing model where advertising and physical capital differ in their reversibility. When the model is simulated using parameters consistent with firms' advertising and capital expenditures, it is able to explain 23.0% of the portfolio return.

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1 Introduction

Firms dedicate a significant share of their funds to advertising. The median publicly listed firm in the United States reported an advertising expense of $9.81 million in 2020, while it spent $12.20 million to purchase physical capital. Arkolakis (2010) estimates that firms' advertising and associated promotional expenses add up to around 4 or 5% of the Gross Domestic Product in the United States. Moreover, these activities are growing in their significance: He, Mostrom, and Sufi (2024) find that industries investing most heavily in customer capital are growing in their share of aggregate revenue and enterprise value. Motivated by such overall importance of advertising activities, I study the effect of advertising on the risk of cash flows, and a firm's expected return.

It is important to note that advertising is a form of investment. Specifically, it may be thought of as an investment specific to building a customer base. Gourio and Rudanko (2014) illustrate how incorporating 'customer capital' in a business cycle model can help explain the dynamics of firms' profits as well as physical investment. Belo, Lin, and Vitorino (2014b) show that firms' brand capital exposures explain the cross section of their equity returns in a similar way to physical capital. It is therefore useful to compare how different are investments in advertising to investments in physical assets.

I propose that advertising intensive firms, or firms with high advertising-to-capital expenditure (Ad-Capex) ratios, are riskier than physical capital intensive counterparts because of the irreversibility of advertising capital. The value of advertising capital is far less to other companies because it contains a highly firm specific element. Moreover, even when firms turn to the market to acquire or sell brands, the exchange process is impaired by the difficulty in estimating its economic value. By contrast, firms are able to sell their excess stock of physical capital if their profitability is low. Such irreversibility makes advertising intensive firms particularly riskier during economic downturns, and lead investors to demand higher expected returns.

Consistent with this view, there exists a significant positive correlation between a firm's Ad-Capex ratio and its future equity return, as visualized by Figure 1. Formally, a long-short quintile portfolio, constructed by buying high Ad-Capex ratio firms and selling low ratio counterparts, generates about 3.89% returns per year. When risk-adjusted using

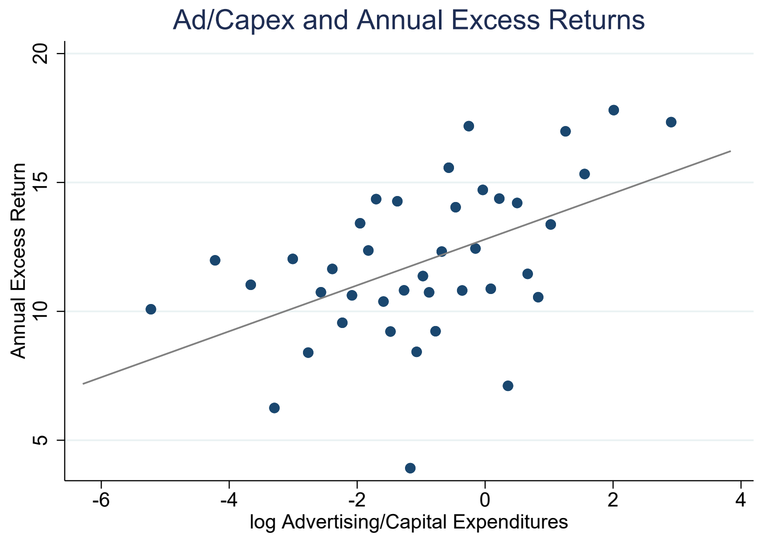


Figure 1: Binned scatterplot, Ad-Capex ratio and annual excess returns.

This figure presents a binned scatterplot, with firms' advertising-to-capital expenditures (Ad-Capex) ratio on the horizontal axis, and 1-year ahead equity returns excess of the 30-day Treasury bill rate (in percent) on the vertical axis. A linear regression is also fitted alongside the bins. The estimates do not contain any covariates, and are drawn following the method by Cattaneo et al. (2022, 2023).

the factor models such as the Fama and French (2015) 5-factor model, the alphas remain significant at about 4.37%.

These return spreads are robust to the changes in the firms' advertising strategies as well as by the data gaps resulting from accounting rule changes. I confirm that the return spread between low and high Ad-Capex firms has become less significant after 1994, when the Securities and Exchanges Commission (SEC) made disclosure rules less stringent. However, I also show that the Ad-Capex ratio still leads to large return spreads in the recent period by using a different data source for advertising expenditures. When the expenditures data compiled from a market research company Vivvix are used to construct the Ad-Capex ratio, the portfolio spread retains its significance with average risk-adjusted return of 7.34% in the post-1994 period.

Having established the importance of the Ad-Capex ratio in explaining the cross section of equity returns, I then introduce a simple neoclassical model of firm investment to explain why firms with greater investments in less reversible capital earn higher returns.

In this model, a firm has access to two independent investment opportunities. Firms can choose to increase their investments in these projects, subject to adjustment costs. Overall, in the simplest case where the production technology is additively separable, it retains features of the classical Hayashi (1982) model.

To study the effects of irreversibility, I consider a parameterization of the model where two investment opportunities are identical in all aspects except for their reversibility during downturns. Therefore, the less reversible input corresponds to advertising, and the reversible input to capital expenditures. This makes ad-intensive firms have more volatile cash flows, and thus investors require higher expected returns.

I conclude with a quantitative exercise of simulating the above model to verify the importance of this effect. When the parameters are disciplined to match the real quantities of capital expenditure and spending in advertisement, the model generates a return spread that is about 23.0% of what is observed in the data.

Literature

Empirically, my paper relates to the vast literature on the cross sectional asset pricing implications of advertising and intangible assets. Previous studies have found that advertising investment rates relative to market capitalization (Chan et al., 2001), or their brand capital (Belo et al., 2014b; Vitorino, 2014) generate significant excess returns. Furthermore, Dou et al. (2021) show heterogeneity in customer capital is equally important, as firms with inalienable customer capital, dependent on talents, are riskier and have higher average returns. Boustanifar and Kang (2024) also find a significant premium among top brand firms as measured by Interbrand. In addition to the literature that emphasizes how advertising is similar to capital expenditures, this paper proposes that advertising *relative* to physical capital investment, or difference between advertising and physical capital, also explains the cross section of equity returns.

Theoretically, my paper is motivated by extensive work on production-based asset pricing with intangible capital. A close and relevant paper is by Kazemi (2021), who emphasizes the importance of asset composition and displacement risk in explaining the cross section of asset returns. In his model, the production technology is also additively separable, and is subject to partial idiosyncratic productivity shocks. However, his model features identical and independently distributed productivity processes, and focuses more on an exogenous aggregate "displacement risk" which is a reallocation shock between the efficiency of the two inputs. My paper complements his findings by showing how the composition of investments can matter even when no reallocation shocks are present, as the two investments could be subject to different degrees of reversibility.

2 Ad-Capex ratio and equity returns

2.1 Data

I study a panel of publicly traded non-financial and non-utilities U.S. firms from 1972 to 2021 that report their advertising and capital expenditures. I use CRSP monthly data for returns, and Compustat Fundamentals Annual for accounting data. Additionally, I supplement the advertising expenses reported on income statements with estimates from Vivvix, an advertising intelligence subsidiary of the London-based market research firm Kantar Group.

Table 1 presents key summary statistics for firms included in my sample. This panel has $72,419$ firm-year observations, from $9,215$ distinct firms. On average, I cover about 37.1% of non-financial and non-utilities firms in Compustat in terms of their market capitalization, and about 31.2% in terms of their total assets.

The relatively small sample size owes to omitting firms that do not report their advertising expenses. While some of this is driven by industrial characteristics,[1] the omission owes much to FRR 44, an accounting rule change that went into effect in 1994 which gave firms substantial discretion in their disclosure (Larkin, 2013; Liang, 2018). I therefore find it more appropriate to assume that the missing expenses should not be considered as zero. While this does not fully resolve potential selection problem in the sample, I address the data gap in greater detail with an alternative advertising data source in Section 3.2.

[1]For example, Yin (2022) finds that 57.4% of retail firms in the Compustat sample report their advertising expenses. On the other hand, only 20.25% of wholesale firms report their advertising.

Table 1: Summary statistics.

The table presents the mean, standard deviation, and key percentiles for selected variables in the CRSP-Compustat sample. Variables are winsorized at the 1st and 99th percentiles. The income statement and balance sheet items in Panel A are in millions of 2015 US dollars, adjusted using the Consumer Price Index from FRED. The ratios in Panel B are calculated using the items in Panel A. Detailed definitions of the variable construction, with reference to variable names, is available on the Appendix.

Panel A: 10-K Items, Capital Stock (Millions 2015 USD)						
	Mean	Std. Dev	P10	P50	P90	N
Ad Expenses	63.72	212.86	0.18	4.04	118.74	72,419
Capital Expenditures	120.65	397.80	0.42	9.85	230.78	72,419
Advertising Capital	413.92	1382.15	1.56	27.70	758.95	68,338
Physical Capital	1282.11	3944.37	9.16	134.00	2509.56	54,746
Sales	2205.35	6425.76	16.80	257.25	4873.63	72,419
Total Assets	2233.12	7179.12	17.03	221.71	4454.49	72,416
Debt	661.07	2238.55	0.00	29.88	1306.43	72,179
Market Capitalization	2754.99	9745.43	13.33	188.95	4776.41	71,321
Panel B: Ratios						
	Mean	Std. Dev	P10	P50	P90	N
Ad-Capex Ratio	2.65	54.20	0.05	0.46	3.45	72,419
Ad Invest Rate	0.17	0.09	0.08	0.15	0.27	68,338
Capex Invest Rate	0.12	0.09	0.03	0.10	0.23	54,746
Brand Capital Share	0.28	0.22	0.04	0.23	0.62	51,847
Gross Profitability	2.02	1.40	1.20	1.59	3.13	72,356
Book-to-Market	0.75	0.79	0.11	0.54	1.70	71,311
Book Leverage	0.24	0.22	0.00	0.21	0.54	72,179
Market Leverage	0.25	0.25	0.00	0.17	0.64	71,084

2.2 Ad-Capex ratio

The resulting distribution of the Ad-Capex ratio is right skewed: while the median Ad-Capex ratio in my sample is about 0.46, the average ratio stands at 1.60. In 2015 US dollar terms, the median firm in my sample spends about 9.85 million dollars in capital expenditures, and 4.04 million dollars in advertising.

Table 2 gives some examples of firms that are high and low in the Ad-Capex ratio. There seems to be some variation at the industry level, with restaurants and accommodation firms being more capex-intensive and consumer product firms being more ad-intensive. However, there is substantial within-industry variation as well. For example, amongst the tech firms, while Facebook made substantial capital expenditures,[2] Netflix (a streaming platform) and Five9 (a cloud contact center solutions company) made large advertisement expenses relative to their physical investment.[3] Overall, a variance decomposition exercise in Table 3, where the log of Ad-Capex ratio is regressed on a series of fixed effects, suggests that the year-industry effects explain about 11% of the total variation in the ratio. By contrast, firm fixed effects account for 74% of the variation. This suggests that the ratio is primarily driven by firm-level, rather than industry characteristics, and that firms change their composition of advertising and capital expenditures as well.

Whether the variation across industries or within industry drives the return spread is discussed in more detail in Section 3. However, the large within-industry variation in the ratio has the potential to explain equity returns, as key cross-sectional patterns such

[2]Facebook's 2016 Annual Report notes: "Cash used in investing activities was $11.74 billion during 2016, mostly due to $7.19 billion for net purchases of marketable securities and $4.49 billion for capital expenditures as we continued to invest in data centers, servers, office buildings, and network infrastructure." The company's revenue in the financial year 2016 was $27.64 billion, of which $26.89 billion was from advertising.

[3]Both companies discuss importance of marketing in their annual reports. Netflix notes advertising and marketing expenses as an essential part of its business throughout its annual report. For example, the company assesses the performance of its business segments using "contribution profit (loss)", defined "as revenues less cost of revenues and marketing expenses incurred by the segment." Five9, Inc. also explains in its Manager's Discussion and Analysis (MD&A) section that: "If we fail to grow our marketing capabilities and develop widespread brand awareness cost effectively, our business may suffer . . . We plan to continue to dedicate significant resources to our marketing programs, including internet advertising, digital marketing campaigns, social marketing, trade shows, industry events, co-marketing with strategic partners and telemarketing."

Table 2: Examples of high and low Ad-Capex ratio firms.

I present firms with high and low capital expenditure to advertisement ratios in year 2016. Capital and advertising expenditures are in millions of 2015 USD.

Company Name	Description	Adv. Exp.	Capital Exp.	Ad-Capex
Advertisement-Intensive Firms				
Five9	Cloud Software	10.7	1.131	9.461
Tempur Sealy	Bedding Products	352.7	62.4	5.652
Netflix	Streaming and Production	842.4	184.83	4.558
Callaway Golf	Golf Equipment	59.003	16.152	3.653
Wayfair	Household Goods Retail	409.125	128.085	3.194
Capex-Intensive Firms				
K2M Group	Medical Products	0.187	17.439	0.0107
Boingo Wireless	Wireless Networks	1.925	107.271	0.0179
Wynn Resorts	Hotels and Casino Resorts	37	1225.943	0.0302
Cheesecake Factory	Food and Restaurants	7.4	115.821	0.0639
Facebook	Social Media and Technology	310	4491	0.0690

Table 3: Variation in Ad-Capex ratios.

I present results of a simple variance decomposition exercise of the Ad-Capex ratio. The log of Ad-Capex ratio, as well as other firm level characteristics, is regressed on a series of fixed effects including year, industry (Fama and French (1997) 17 industries), year-industry, and firm level indicators. The R-squareds from these regressions are presented to show the percentage of variation captured by fixed effects.

Variation (%)	Year	Industry	Year-Industry	Firm
log Ad-Capex	1.40	8.06	11.09	74.35
Ad-Capex	0.12	0.13	0.01	25.15
log Ad	1.82	10.91	14.36	90.46
log Capex	2.97	6.10	10.57	87.77
Brand Capital Share	0.76	13.43	16.01	89.21
Gross Profitability	4.51	11.29	16.80	79.32
Market Leverage	7.68	11.02	18.78	68.49
Book-to-Market	18.90	4.28	23.72	56.04

as the value premium are primarily within-industry (Cohen et al., 2003; Campbell et al., 2023).

2.3 Advertising and Physical Capital Stocks

Moreover, in addition to flows of advertising and capital expenditures, which are readily available accounting items, stocks of advertising and physical capital are estimated using the perpetual inventory method as in Belo et al. (2014b).

The method estimates stocks of firms' advertising capital by first assuming an initial value of firms' advertising capital stock in its first year by the equation:

$$K_{1,1} = \frac{I_{1,1}}{\delta_1} \tag{1}$$

where $I_{1,1}$ is the firms' first available advertising expense, and δ_1 is an exogenously assumed depreciation rate of advertising capital follows Gourio and Rudanko (2014) set at $\delta_1 = 0.15$.[4] Then the subsequent advertising capital stocks are populated by iterating the capital accumulation equation forward:

$$K_{1,t+1} = (1 - \delta_1)K_{1,t} + I_{1,t}. \tag{2}$$

As presented in Table 1, the resulting median stock of advertising capital in the sample is about \$27.7 million, or about 20% of physical capital. Moreover, the average investment rates for advertising and physical capital, or the ratio between current period's investment and stock of capital, are 17% and 12% respectively.

2.4 Portfolio returns

At the end of June of each year, I form five equally weighted portfolios of stocks based on their issuing companies' advertising expenses to capital expenditures from their latest

[4]The authors use estimates annual customer turnover rates in supermarkets from Bronnenberg et al. (2012). Yet, there is a large variation in the depreciation rate of advertising capital. Several studies, including Belo et al. (2014b)'s initial specification, adopt depreciation rates of 50% from Lambin (1976). However, lower rates of 15 to 20% from Belo et al. (2022) are also frequently used. Nevertheless, the main empirical results remain unaffected as they use advertising expenditures rather than capital stock.

financial statements. Since the portfolio is rebalanced in June, I only include firms whose fiscal year ends in December to ensure that the accounting information is observable to investors. As previously stated, I exclude financial and utility firms following the convention in the empirical asset pricing literature.[5] However, the results are robust to their inclusion as well. As a result, I obtain five portfolios with a median portfolio having 85 firms in a given year[6], and covering 23 out of 48 the Fama and French (1997) industries.[7]

Table 4 presents the results. Panel A shows that the portfolio returns decrease in the investment ratio. The lowest quintile portfolio earns 9.49% annualized returns, whereas the highest quintile portfolio earns 13.38%. A long-short portfolio that buys the lowest percentile and sells the highest would earn an average return of 3.89% per year.

This pattern is also evident in risk-adjusted returns. Panels B and C present estimates for the CAPM and the Fama and French (2015) 5-factor models. The alphas for both specifications are significant at 5.13% and 4.37% respectively. They are generated from the long, rather than the short end of the portfolio as well, thereby suggesting that the long-short returns are not likely to be subsumed by transaction costs. The lowest portfolio has a 0.00% Fama and French (2015) alpha, whereas the highest Ad-Capex portfolio has an 4.37% alpha.

Interestingly, the market betas estimates from both models exhibit an opposite pattern to the risk-adjusted returns. The long-short portfolio has significant negative loadings on the market risk premium at around -0.15 for both CAPM and Fama and French (2015) models. The risk-adjusted alphas are larger than the excess returns as a result. This points to the possibility that the observed excess returns are not driven by an unconditional correlation between the portfolios and the market. By contrast, the long-short portfolio does not have significant loadings for other factors including size, value, profitability, and investment. However, because the risk-adjusted alphas remain significant, the portfolio

[5]Firms with SIC codes 4800-4999, 6000-6999. A common reasoning is that as highly regulated and levered industries, the financial and utilities sectors may require a different framework from the neoclassical theory of investment.

[6]The number is lowest in 1994 at 31.

[7]Kenneth French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html) contains definitions of the industry classifications.

Table 4: Portfolio returns, equal-weighted, univariate sort.

Panel A presents annualized (×12) monthly returns in excess of 30-day Treasury bill rate for 5 equally-weighted portfolios of Ad-Capex ratios and for the long-short portfolio (High – Low). The (High – Low) portfolio sets a long position for high Ad-Capex ratio firms and sells short low Ad-Capex ratio firms. Row [t] contains t-statistics calculated using Newey-West standard errors. Row SR reports the annualized Sharpe Ratio for each portfolio. Panels B and C tabulate estimates from the CAPM and Fama and French (2015) 5-factor models respectively. α and α_{ff} denote model intercepts, or average portfolio abnormal returns. Each of β_{mkt}, β_{smb}, β_{hml}, β_{rmw}, β_{cma} coefficients corresponds to a factor loading for the market, size, book-to-market, profitability, and investment.

Panel A: Returns excess of the 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.49	11.02	12.20	12.14	13.38	3.89
[t]	(2.45)	(3.11)	(3.43)	(3.29)	(3.38)	(2.33)
SR	0.11	0.14	0.15	0.15	0.16	0.11

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	-0.69	1.33	2.76	2.98	4.44	5.13
[t]	(-0.35)	(0.75)	(1.57)	(1.52)	(1.86)	(3.11)
β	1.31	1.25	1.21	1.18	1.15	-0.16
[t]	(30.77)	(32.90)	(28.61)	(29.28)	(22.80)	(-6.14)
R^2	0.72	0.73	0.70	0.67	0.59	0.07

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	0.00	0.94	1.99	2.32	4.37	4.37
[t]	(0.00)	(0.67)	(1.27)	(1.44)	(2.04)	(2.59)
β_{mkt}	1.13	1.10	1.08	1.04	0.98	-0.15
[t]	(32.21)	(35.88)	(27.71)	(30.44)	(21.94)	(-5.37)
β_{smb}	0.83	0.82	0.81	0.82	0.90	0.07
[t]	(10.79)	(12.95)	(10.18)	(9.85)	(9.50)	(1.26)
β_{hml}	0.17	0.14	0.23	0.20	0.20	0.03
[t]	(2.43)	(2.12)	(3.41)	(2.70)	(2.31)	(0.37)
β_{rmw}	-0.30	-0.17	-0.09	-0.13	-0.27	0.03
[t]	(-2.64)	(-1.66)	(-0.80)	(-1.07)	(-1.72)	(0.26)
β_{cma}	-0.20	-0.07	-0.13	-0.10	-0.10	0.09
[t]	(-1.49)	(-0.51)	(-0.88)	(-0.77)	(-0.54)	(0.69)
R^2	0.87	0.87	0.84	0.82	0.77	0.08

Table 5: Portfolio characteristics.

The table presents the median firm-level characteristics of 5 portfolios used in Table 4. Each year, medians of characterisitcs in each portfolio are obtained, and averaged across the sample period. The variable definitions are identical to those in Table 1, and described in the Appendix.

Portfolios	Low	2	3	4	High
Ad-Capex	0.048	0.180	0.421	0.997	3.580
Ad Investment Rate	0.142	0.151	0.155	0.158	0.158
Capex Investment Rate	0.139	0.118	0.106	0.099	0.077
Brand Capital Share	0.045	0.121	0.219	0.378	0.603
Gross Profitability	1.600	1.639	1.612	1.643	1.815
Market Leverage	0.204	0.196	0.187	0.179	0.154
Book-to-Market	0.570	0.603	0.599	0.574	0.601

returns could contain characteristics that are over and beyond traditional measures of duration such as the market-to-book ratio.

A closer look at Table 5 reveals differences in characteristics of firms in each portfolio. The table presents median firm characteristic of firms in each portfolio in years of portfolio formation, and then averaged across the sample period.

Consistent with the notion of Ad-Capex ratio, ad-intensive firms tend to advertise more but make less capital expenditures. They also generally have greater shares of advertising capital, as the differences in investmet rates tend to be persistent.[8] Moreover, while the ad-intensive firms higher levels of gross profitability, they do not show significant differences in leverage or book-to-market ratios from capex-intensive firms. This is consistent with the notion that advertising tends to be more aggressive for high-markup products (Hall, 2014), and the ratio may be capturing the profitability premium (Novy-Marx, 2013). However, the small difference in other financial ratios points to the possibility that the Ad-Capex ratio spread is not a proxy for the value premium.

Table 6 provides additional evidence that these excess returns are not driven by valuation ratios alone. It reports estimates of a predictive regression of one year ahead stock

[8]The transition matrix of portfolios in the Appendix (Table A1) shows that the likelihood of a firm being in the same Ad-Capex portfolio quintile as in the previous year ranges between 52 to 75%.

Table 6: Annual predictive regressions.

$$R_{jt+1} = \alpha_j + \delta_t + \beta_1 \log \mathrm{Ad}_{jt}/\mathrm{Capex}_{jt} + \gamma X_{jt} + \varepsilon_{jt+1}.$$

The table reports estimates from predictive regressions of firm level stock returns using five different specifications. Column (1) presents results for a univariate regression with firm fixed effects, and (2) augments (1) with year fixed effects. Column (3) and (4) report predictive regression results for gross profitability and log book-to-market ratios. Column (5) includes all three variables as predictors. For all specifications, the t-statistics, calculated using firm-year clustered standard errors, are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
log Ad-Capex	3.523***	3.942***			3.377***
	(4.41)	(6.09)			(5.15)
Gross Profitability			-0.738		0.0294
			(-0.89)		(0.04)
log Book-to-Market				15.29***	15.07***
				(10.77)	(10.58)
adj. R-sq	-0.00339	0.132	0.130	0.148	0.150
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	30567	30567	30549	29250	29234

* $p < .10$, ** $p < .05$, *** $p < .01$

returns on the Ad-Capex ratio at the firm level. Column (2) shows that an increase in a firm's log Ad-Capex ratio from the median to the 90th percentile is associated with 14.30% higher annual returns at the stock level.[9] This effect is smaller, but comparable to that of book-to-market ratio.[10]

3 Discussion of empirical findings

In the following section, I investigate further to understand whether the Ad-Capex returns are driven by industry-specific patterns, or are affected by changes in accounting rules about advertising expenses.

[9] $14.30 \approx 3.377 \times (\log(3.45) - \log(0.05))$
[10] $41.26 \approx 15.07 \times (\log(1.70) - \log(0.11))$

Table 7: Ad-Capex ratios by industry.

The following table presents the average Ad-Capex ratio, share of advertising capital, and market leverage by each of the 17 Fama and French (1997) industries.

Industry	Ad-Capex Ratio	Ad Capital Share	Market Leverage
Food	.902	.365	.188
Mining and Minerals	.346	.11	.301
Oil and Petroleum	.235	.089	.246
Textiles and Apparel	1.346	.467	.235
Consumer Durables	1.043	.372	.219
Chemicals	.209	.099	.292
Drugs, Soaps, Perfumes	1.301	.437	.102
Construction	.561	.251	.325
Steel Works	.234	.099	.342
Fabricated Products	.309	.171	.074
Machinery and Bus. Equipment	.301	.166	.138
Automobiles	.237	.191	.315
Transportation	.146	.078	.438
Retail Stores	.612	.271	.222
Others	.424	.203	.155

3.1 Industry adjustments

To understand their sources, it is important to distinguish whether the return spreads observed in the previous section are driven by within, or across-industry characteristics. While most of the variation in ad-capex ratios is within-industry, there also exists significant across-industry variation. As shown on Table 7, textiles and consumer durables tend to be ad-intensive, whereas chemicals and steel works tend to have low Ad-Capex ratios as well as low share of advertising capital.

Table 8 presents results of the within-industry sort using Fama and French (1997) 17 industry portfolios. The numbers are very similar to the baseline results in Table 4, with ad-intensive firms having higher average returns, both raw and risk-adjusted, than capex-intensive counterparts. This suggests that the documented Ad-Capex ratio spread is driven primarily by within-industry variation, and points towards an industry equilibrium model as a potential explanation.

Table 8: Portfolio returns, equal-weighted and industry adjusted.

The Table presents excess and risk-adjusted annualized ($\times 12$) monthly returns for 5 equally-weighted portfolios of Ad-Capex ratios and for the long-short portfolio (High − Low) within 17 Fama and French industries.

Panel A: Returns excess of 30-day Treasury bill rate

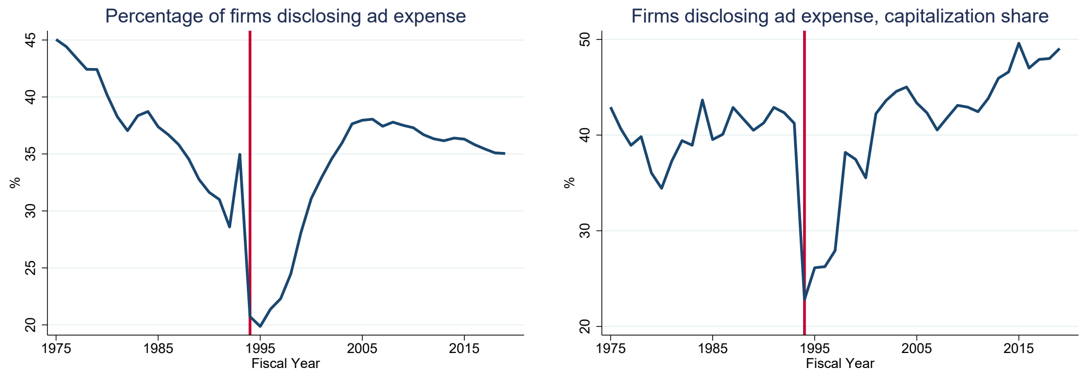
Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.61	11.59	11.33	12.63	13.48	3.87
[t]	(2.51)	(3.38)	(3.19)	(3.46)	(3.23)	(2.51)
SR	0.12	0.15	0.14	0.16	0.15	0.11

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	-0.20	2.09	1.80	3.48	4.14	4.34
[t]	(-0.10)	(1.25)	(1.02)	(1.85)	(1.60)	(2.87)
β	1.26	1.22	1.23	1.18	1.20	-0.06
[t]	(30.94)	(36.02)	(27.80)	(30.09)	(21.40)	(-1.79)
R^2	0.72	0.75	0.71	0.69	0.56	0.01

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	-0.51	1.70	1.54	2.64	5.10	5.61
[t]	(-0.37)	(1.19)	(0.95)	(1.75)	(2.17)	(3.15)
β_{mkt}	1.10	1.09	1.08	1.04	0.98	-0.12
[t]	(34.95)	(34.45)	(29.87)	(31.23)	(19.87)	(-3.61)
β_{smb}	0.86	0.74	0.78	0.80	0.99	0.13
[t]	(12.24)	(10.87)	(10.05)	(10.05)	(9.37)	(2.40)
β_{hml}	0.15	0.15	0.23	0.19	0.18	0.03
[t]	(2.34)	(2.06)	(3.35)	(2.77)	(1.85)	(0.41)
β_{rmw}	-0.18	-0.12	-0.14	-0.16	-0.41	-0.22
[t]	(-1.81)	(-1.16)	(-1.16)	(-1.40)	(-2.23)	(-2.02)
β_{cma}	-0.08	-0.10	-0.19	-0.03	-0.19	-0.11
[t]	(-0.72)	(-0.81)	(-1.25)	(-0.20)	(-0.86)	(-0.70)
R^2	0.87	0.87	0.84	0.84	0.76	0.07



(a) Share in number of firms (b) Share in stock market capitalization

Figure 2: Advertising disclosure share.
This figure presents two time series plots of share of firms that disclose their advertisement expenses in 10-K filings. Left subfigure plots shares in number of firms. Right subfigure plots as percentage of total market capitalization. The red line is drawn for year 1994, the year in which FRR 44 was released by the SEC, relaxing disclosure requirements for advertisement expenses.

3.2 Data gaps in advertising

Another concern about the results is about the use of accounting data to measure advertising expenses. Unfortunately for the researcher, advertising expenses are one of sparsely populated items in firms' financial statements. Therefore, there is a possibility that the return spread is driven by the data gap in advertising expenses.

Before 1994, all firms that made substantial advertising spending – more than 1% of sales – had to report their advertising expenses (SEC Reg. 210.12-11). However in 1994, the SEC gave firms substantial discretion. The newly introduced Financial Reporting Release (FRR 44) allowed firms not to disclose their advertising spending. This was intended to reduce "costs of reporting by public companies without loss of material information necessary to protect investors (Simpson, 2008; Moon et al., 2023)."[11] A large number of firms took advantage of this rule change and decided not to disclose, as shown by the decreasing share of firms that report their advertisement expenses in Figure 2.

The lower coverage ratio leads to reducing the significance of the returns generated by Ad-Capex portfolios in the post-1994 period. Table 9 reports the portfolio excess returns

[11]Please refer to the papers for a discuss both benefits and costs of non-disclosure to the investors. However, the normative implications are beyond the scope of this paper.

Table 9: Portfolio returns, pre- and post-1994.

Panels A and B respectively present pre- and post-1994 annualized ($\times 12$) monthly returns in excess of 30-day treasury bill rate for 5 equally-weighted portfolios of Ad-Capex ratios and for the long-short portfolio (High – Low). The (High – Low) portfolio sets a long position for high Ad-Capex ratio firms and goes short for low Ad-Capex ratio firms. Row [t] contains t-statistics calculated using Newey-West standard errors. Row SR reports the annualized Sharpe Ratio for each portfolio.

Panel A: Returns excess of the 30-day Treasury bill rate, pre-1994

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.93	11.33	12.22	12.24	13.59	3.66
[t]	(1.89)	(2.20)	(2.40)	(2.38)	(2.54)	(1.99)
SR	0.13	0.15	0.16	0.17	0.19	0.12

Panel B: Returns excess of the 30-day Treasury bill rate, post-1994

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.11	10.80	12.17	12.05	13.20	4.09
[t]	(1.63)	(2.21)	(2.45)	(2.30)	(2.31)	(1.55)
SR	0.10	0.13	0.15	0.14	0.15	0.11

in the pre- and post-1994 sub-samples. Full tables including risk-adjusted returns are presented in Tables A4 and A5 of the appendix. The results show that the relationship between Ad-Capex ratio and expected returns is far stronger in the pre-1994 than the post-1994 data. While the annualized excess returns of the long-short portfolio is 3.66% in the earlier subsample, it is 4.09% and statistically less significant in the post-1994 period.

However, further analyses show that such difference is unlikely to be from changes in the fundamental linkage between the investment composition and expected return. Table 10 presents results of a panel regression of one year ahead returns on the log of Ad-Capex ratio, interacted with an indicator for the post-1994 period observations. The small and insignificant coefficient on the interaction term suggests that there are little changes in sensitivities. The positive relationship between Ad-Capex ratio and one year ahead annual stock returns noted in Table 6 is still present.

The relationship between Ad-Capex ratio and excess returns appears in the post-1994

Table 10: Annual predictive regressions, pre- and post-1994.

$$R_{jt+1} = \alpha_j + \delta_t + \beta_1 \log \mathrm{Ad}_{jt}/\mathrm{Capex}_{jt} + \beta_2 \mathrm{Post}_t \times \log \mathrm{Ad}_{jt}/\mathrm{Capex}_{jt} + \gamma X_{it} + \varepsilon_{it+1}.$$

The table reports estimates from predictive regressions of annual firm level stock returns using five different specifications in a similar specification to Table 6. All specifications include Post, an indicator variable for years including and after 1994, log Ad-Capex ratio, and an interaction term of the two variables. Column (1) only includes firm fixed effects, and (2) augments (1) with year fixed effects. Column (3) includes gross profitability (Novy-Marx, 2013) and log book-to-market ratios to Column (2). Columns (4) and (5) report predictive regression results for the cash flow duration and market-to-book ratios. For all specifications, the t-statistics are calculated using standard errors clustered at firm-year levels.

	(1)	(2)	(3)	(4)	(5)
Post	-10.27*			-5.366	
	(-1.70)			(-0.85)	
log Ad-Capex	3.284**	4.267***	3.377***	2.599*	3.577***
	(2.62)	(4.77)	(5.15)	(1.95)	(3.84)
Post × Ad-Capex	0.486	-0.539		0.626	-0.332
	(0.38)	(-0.50)		(0.47)	(-0.30)
Gross Profitability			0.0294	0.177	0.0358
			(0.04)	(0.20)	(0.04)
log Book-to-Market			15.07***	18.70***	15.06***
			(10.58)	(10.18)	(10.56)
adj. R-sq	-0.00214	0.132	0.150	0.0258	0.150
Firm FE	No	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	30567	30567	29234	29234	29234

* $p < .10$, ** $p < .05$, *** $p < .01$

period if alternative sources for advertisement expenses are used instead. I construct portfolios using the identical steps but with annual advertising expenses compiled from Kantar Vivvix.[12] The firm level expenditure estimates from Vivvix are matched by names following the steps described in Section A.7 of the appendix. Table 11 presents the portfolio returns in excess of the risk-free rate as well as as the risk-adjusted returns. While the unadjusted long-short portfolio and the risk-adjusted CAPM alpha are weakly significant with t-statistics of 1.74 and 1.63 respectively, the Fama and French (2015) five-factor annualized alpha is strongly significant at 7.34%.

4 Model

In this section, I propose a simple neoclassical model of firm investment to explain the findings from earlier sections, on why advertising intensive firms have higher expected returns.

4.1 Setup

I consider a partial equilibrium model of a discrete time economy populated by a continuum of firms. Each firm in industry maximizes its expected present value of cash flows by using two factors of production: advertising and physical capital.

Technology

As all firms in the economy have identical structure, I omit indexes for firms. A firm produces operating cash flows by using a decreasing returns-to-scale technology with two inputs $K_{1,t}$ and $K_{2,t}$. It is exposed to an aggregate shock X_t as well as idiosyncratic shocks $Z_{1,t}$ and $Z_{2,t}$. These shocks are observable to the firm prior to their investment decisions at time t.

$$F(Z_{1,t}, Z_{2,t}, X_t, K_{1,t}, K_{2,t}) = a_1 X_t Z_{1,t} K_{1,t}^{\alpha} + a_2 X_t Z_{2,t} K_{2,t}^{\alpha}. \tag{3}$$

For simplicity, I consider a simple, additively separable technology as in Eisfeldt and Papanikolaou (2013) and Kazemi (2021) with the same decreasing returns to scale α for

[12]The database was also known previously as Kantar AdSpender and Advertising Insights: https://www.kantar.com/expertise/advertising-media-pr/advertising-intelligence/advertising-insights.

Table 11: Portfolio returns, equal-weighted, ad expenditures from Vivvix.

The Table presents excess and risk-adjusted annualized ($\times$12) monthly returns for 5 equally-weighted portfolios of Ad-Capex ratios and for the long-short portfolio (High − Low). The portfolios follow the same step to construct, except that advertisement expenditures are obtained using estimates from Vivvix (formerly Kantar AdSpender). All Panels are organized in the same way as Table 4.

Panel A: Returns excess of 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	10.26	12.68	14.99	12.29	15.53	5.26
$[t]$	(2.02)	(2.54)	(2.73)	(2.18)	(2.76)	(1.38)
SR	0.13	0.16	0.18	0.15	0.18	0.10

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	1.19	2.91	5.08	2.78	6.21	5.02
$[t]$	(0.48)	(1.59)	(1.96)	(1.06)	(1.84)	(1.31)
β	1.26	1.36	1.38	1.32	1.29	0.03
$[t]$	(18.68)	(27.83)	(26.38)	(31.21)	(24.62)	(0.37)
R^2	0.78	0.83	0.77	0.73	0.65	0.00

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	-1.36	1.73	4.58	3.07	5.98	7.34
$[t]$	(-0.75)	(1.25)	(2.04)	(1.37)	(2.45)	(2.61)
β_{mkt}	1.26	1.28	1.26	1.15	1.12	-0.15
$[t]$	(25.36)	(28.18)	(21.64)	(29.49)	(17.28)	(-1.98)
β_{smb}	0.34	0.46	0.48	0.63	0.74	0.40
$[t]$	(3.29)	(4.33)	(4.25)	(6.10)	(5.54)	(4.53)
β_{hml}	0.44	0.28	0.23	0.11	-0.01	-0.45
$[t]$	(6.26)	(4.33)	(2.49)	(1.71)	(-0.09)	(-4.77)
β_{rmw}	0.25	0.00	-0.16	-0.17	-0.13	-0.38
$[t]$	(2.37)	(0.03)	(-1.06)	(-1.82)	(-1.05)	(-3.60)
β_{cma}	-0.06	0.00	0.09	-0.09	-0.02	0.04
$[t]$	(-0.54)	(0.01)	(0.46)	(-0.46)	(-0.12)	(0.25)
R^2	0.86	0.89	0.84	0.83	0.78	0.41

both inputs[13]. However, the setup could extend to more general production functions that feature substitutability or complementarity between the two inputs as in Belo et al. (2014a, 2017).

Idiosyncratic shocks Z_t

The output is subject to two idiosyncratic productivity shocks that are uncorrelated across firms. These shocks are persistent and follow log AR(1) processes:

$$\log Z_{1,t+1} \equiv z_{1,t+1} = \rho_{1,z} z_{1,t} + \sigma_{1,z} \varepsilon_{1,t+1}, \tag{4}$$

$$\log Z_{2,t+1} \equiv z_{2,t+1} = \rho_{2,z} z_{2,t} + \sigma_{2,z} \varepsilon_{2,t+1}. \tag{5}$$

ρ_* and σ_* respectively denote persistence and volatility of the idiosyncratic productivity, and ε_* is the i.i.d standard normal shock component. Such persistence ensures that firms with high productivity are more likely to invest, as the productivity is expected to be higher in the next period as well.

Investment and Adjustment Costs

While both $K_{1,t}$ and $K_{2,t}$ depreciate at rates δ_1 and δ_2, firms can alter their stock of capital through investment.

$$K_{1,t+1} = (1-\delta_1)K_{1,t} + I_{1,t}, \qquad I_{1,t} \geq 0.$$
$$K_{2,t+1} = (1-\delta_2)K_{2,t} + I_{2,t}.$$

For both types of capital, positive investments entail convex adjustment costs: with larger investment rates leading to higher marginal costs per unit of additional capital. One key difference, however, is that advertising capital $K_{1,t}$ is irreversible: the only way firms can reduce the stock of their $K_{1,t}$ is letting it depreciate through zero investment $I_{1,t}$.

[13] The decreasing returns to scale assumption is needed to generate a stationary distribution of firm size at the simulation.

$$C_1(I_{1,t}, K_{1,t}) = \frac{c_1}{2}\left(\frac{I_{1,t}}{K_{1,t}}\right)^2 K_{1,t}, \qquad I_{1,t} \geq 0. \tag{6}$$

$$C_2(I_{2,t}, K_{2,t}) = \frac{c_2}{2}\left(\frac{I_{2,t}}{K_{2,t}}\right)^2 K_{2,t}. \tag{7}$$

Aggregate Productivity X_t and SDF M_{t+1}

Additionally, the firms in the economy are exposed an aggregate total factor productivity shock. A disembodied productivity X_t affects both terms in the production function, as shown in Equation (3), and follows an AR(1) process with persistence λ and conditional standard deviation σ_x.

$$\log X_{t+1} \equiv x_{t+1} = \lambda x_t + \sigma_x \varepsilon_{x,t+1}. \tag{8}$$

As this is a partial equilibrium model, I assume an exogenously specified stochastic discount factor (SDF) as in Zhang (2005). All firms in the economy are owned by a representative investor who evaluates future cash flows using the following SDF:

$$\log M_{t,t+1} = \log \beta \ - \gamma \Delta x_{t+1}. \tag{9}$$

The parameter $\gamma_x > 0$ is the sensitivity of the discount factor to the aggregate shock X_t, or price of risk. In a general equilibrium model, the parameter would be equivalent to risk aversion of the representative investor. The negative loading on the aggregate shock Δx_{t+1} implies that future cash flows are discounted more heavily when the economy is expected to grow ($\Delta x_{t+1} > 0$), or it is currently in recession ($x_t < x_{t+1}$).

4.2 Model solution

Overall, firms in the economy solve the following optimization problem:

$$\max_{K_{1,t+1}, K_{2,t+1}} \sum_{t=0}^{\infty} \mathbb{E}_0 M_t \Pi(K_{1,t}, K_{2,t}, Z_{1,t}, Z_{2,t}, X_t) \tag{10}$$

subject to:

$$\Pi(K_{1,t}, K_{2,t}, Z_{1t}, Z_{2t}, X_t) = F(Z_{1,t}, Z_{2,t}, X_t, K_{1,t}, K_{2,t}) - I_{1,t} - I_{2,t} - C_1(I_{1,t}, K_{1,t}) - C_2(I_{2,t}, K_{2,t}), \tag{11}$$

$$K_{1,t+1} = (1-\delta_1)K_{1,t} + I_{1,t}, \tag{12}$$

$$K_{2,t+1} = (1-\delta_2)K_{2,t} + I_{2,t}, \tag{13}$$

$$K_{1,t+1} \geq 0, \qquad K_{2,t+1} \geq 0, \qquad I_{1,t} \geq 0. \tag{14}$$

The firm's problem can be re-written recursively as follows:

$$V(K_1, K_2, Z_1, Z_2) = \max_{I_1, I_2} \Pi(K_1, K_2, Z_1, Z_2, X) + \mathbb{E}[m'V'(K_1', K_2', Z_1', Z_2')], \tag{15}$$

$$m' = {}^{M'}/_{M}, \tag{16}$$

$$I_1 = K_1' - (1-\delta_1)K_1, \tag{17}$$

$$I_2 = K_2' - (1-\delta_2)K_2, \qquad I_1 \geq 0. \tag{18}$$

Rearranging the above expression to be consistent with an asset pricing equation $\mathbb{E}[\frac{M_{t+1}}{M_t} R_{t+1}] = 1$ as in Cochrane (2005), the gross return can be expressed as:

$$R(K_1', K_2', Z_1', Z_2', X') = \frac{V(K_1', K_2', Z_1', Z_2', X')}{V(K_1, K_2, Z_1', Z_2', X') - \Pi(K_1, K_2, Z_1, Z_2, X)}. \tag{19}$$

5 Mechanism

To illustrate the effect of differences in reversibility, I consider a baseline case where the two production technologies are identical, but differ only in the nonnegativity constraint $I_{1,t} \geq 0$. Therefore, other parameters such as returns to capital ($a_1 = a_2$), depreciation rates ($\delta_1 = \delta_2$), adjustment costs ($c_1 = c_2$), and unconditional variance of the productivity processes ($\frac{\sigma_1^2}{1-\rho_1^2} = \frac{\sigma_2^2}{1-\rho_2^2}$) are assumed to be equal.

The policy functions, calculated numerically from the above setup, suggest that the investment ratio is more sensitive to changes in Z_1 than that of Z_2. The two plots in

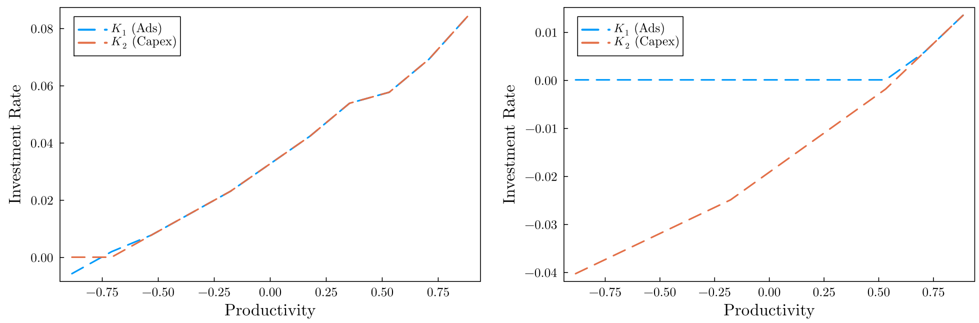


Figure 3: Policy functions of investment rates I/K, by firm-specific productivity levels Z for high aggregate state (Left) and low aggregate state (Right).

Figure 3 show how the investment ratio changes for different values of Z_1 and Z_2, with levels of the other held fixed. The left panel shows that as Z_1 becomes higher, firms would increase its relative investment in the first input, thus leading to higher I_1/I_2. However, the change in the ratio due to lower levels of Z_2 represented by parallel shifts in the curve from the yellow to the blue line is relatively smaller.

6 Quantitative analysis

I now consider the quantitative implications of the model by calibrating it to match the aforementioned empirical findings. To be consistent with the empirical setup, I also refer to the investment in the first input as capital expenditures and the second input as advertising.

6.1 Parameterization

I parameterize the model at an annual frequency, as in Table 12, and solve the model numerically.

The time discount factor is set to $\beta = 0.98$, which corresponds to an annual risk-free rate of 2.4%. The parameter γ_x in the SDF equation (9) is used to match the magnitude of the equity premium in the model. Together with the parameterizations of the aggregate TFP process discussed in the previous paragraph, it is set to $\gamma_x = 6.75$, setting an upper bound for the annualized Sharpe ratio of 0.4 (Hansen and Jagannathan, 1991).

Table 12: Parameterization used for quantitative analysis.

The table lists the parameters used for the quantitative exercise in Section 6.

Parameter	Value	Description
α	0.60	Returns to scale
c_1	6.0	Adjustment cost parameter for input 1
c_2	6.0	Adjustment cost parameter for input 2
δ_1	0.15	Depreciation rate of the first capital stock
δ_2	0.15	Depreciation rate of the second capital stock
ρ_1	0.7	Persistence of the productivity process for input 1
ρ_2	0.7	Persistence of the productivity process for input 2
σ_1	0.2	Conditional volatility of the productivity process for input 1
σ_2	0.2	Conditional volatility of the productivity process for input 2
γ_x	6.75	Loading on the stochastic discount factor
β	0.98	Time discount factor
λ	0.90	Persistence of the aggregate TFP process
σ_x	0.005	Conditional volatility of the aggregate TFP process

For setting the parameters related to the first input, I use the standard calibrations from the production-based asset pricing with physical capital. The depreciation rate is set to be $\delta_1 = 0.15$, in line with the NIPA estimates. For the second input, I also adopt a more conservative value for the depreciation rate of advertising capital K_2 at $\delta_2 = 0.15$ as in Gourio and Rudanko (2014) and Belo et al. (2014b). This is in turn consistent with the findings from Bronnenberg et al. (2012) showing that revealed brand preferences based on consumer migration change very slowly. The persistence and volatility of the productivity process Z_1 are set as $\rho_1 = 0.7$ and $\sigma_1 = 0.2714$ each, using firm-level productivity estimates from Imrohoroglu and Tuzel (2011).

6.2 Simulation Results

I present the simulated results in Table 13. As in the data, the higher Ad-Capex ratio firms have higher realized returns; and a long-short portfolio generates about 0.98% annual returns, which is about 23.0% of the magnitude in the data.

Table 13: Simulated portfolio returns and data

The table reports portfolio returns simulated from the model following the steps in Section 6.1.

Excess Returns	Low	2	3	4	High	High-Low
Model	6.51	6.73	6.75	6.85	7.40	0.89
Data	9.50	11.02	12.19	12.13	13.37	3.87

7 Conclusion

To conclude, this paper proposes that advertising expenditures relative to capital investments are informative about the cross section of equity returns. When a portfolio is formed by purchasing firms with high Ad-Capex ratios and selling low Ad-Capex ratio counterparts, it generates significant risk-adjusted returns. These returns are still present when industries are controlled for, and with an alternative data source of advertising expenditures. A production-based asset pricing model where two inputs have different degrees of reversibility is able to generate this return spread.

An area to consider in future work will be general equilibrium implications of the Ad-Capex ratio. A rich literature has shown that asset return dynamics such as time-varying risk premiums can emerge in a general equilibrium setting when there are multiple sources of cash flows (Cochrane et al., 2008; Eberly and Wang, 2012; Martin, 2013). While the current model did not consider these effects due to its focus on the cross section, it would be interesting to study how the risk premium and firm investments are set in this environment.

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A Appendix

A.1 Variable Definitions

- Sales: Compustat Item `SALE`.
- Capital Expenditures: Compustat Item `CAPX`.
- Advertising Expenses: Compustat Item `XAD`.
- Total Assets: Compustat Item `AT`.
- Brand Capital: Constructed using the perpetual inventory method. Initial brand capital stock $K_{1,0}$ is set as:

  $$K_{1,0} = \frac{\texttt{XAD}_t}{\delta_1}$$

  It is then iterated using the capital accumulation equation, using a fixed depreciation rate of $\delta = 0.15$:

  $$K_{1,t+1} = (1 - \delta)K_{1,t} + \texttt{XAD}_t$$

- Property, Plant, and Equipment: Compustat Item `PPEGT`.
- Debt: Sum of debt in current liabilities (Compustat: `DLC`) and long-term debt (Compustat: `DLTT`).
- Market Capitalization: product of the number of shares outstanding (Compustat: `CSHO`) and the closing price (Compustat: `PRCC_F`).
- Consumer Price Index: Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (FRED: `CPIAUCSL`)
- Book-to-Market ratio: follows Fama and French (1992, 1993).

A.2 Transition Probabilities of Ad-Capex Portfolios

Table A1: Transition probabilities of five Ad-Capex portfolios.

The table presents annual transition probabilities for Ad-Capex portfolios.

Ad-Capex Pfo $t/t+1$	1	2	3	4	5	Total
1	75.00	18.51	4.05	1.72	0.72	100.00
2	17.56	55.13	20.91	4.84	1.55	100.00
3	3.47	20.38	52.03	20.17	3.96	100.00
4	1.30	4.49	20.04	55.83	18.34	100.00
5	0.96	1.54	3.77	18.53	75.19	100.00
Total	19.29	20.12	20.40	20.38	19.81	100.00

A.3 Correlations between Portfolios

Table A2: Correlations between Ad-Capex long-short portfolio and other portfolios.

The table presents pairwise correlations of monthly returns between the Ad-Capex long-short portfolio and other portfolios. *LS* is the return from a long-short portfolio based on the Ad-Capex ratio. *MKT* is the market risk premium, or the return on the CRSP value-weighted portfolio in excess of the 30-day Treasury bill rate. *SMB*, *HML*, *CMA*, *RMW* are size, book-to-market, investment, and profitability factors, which together with *MKT* make the Fama and French (2015) 5-factor model. *MOM* is the momentum factor (Jegadeesh and Titman, 1993; Carhart, 1997). HML^{INT} is the intangible-adjusted value factor from Eisfeldt et al. (2022). IA^{HXZ}, ROE^{HXZ}, and EG^{HXZ} are investment, profitability, and expected growth factors from Hou et al. (2021). The Fama and French (2015) factors and the momentum factor are available from the Kenneth French's Data Library; the intangible-adjusted series is uploaded on Edward Kim's GitHub Page; the q-factor portfolios are available from the Hou-Xue-Zhang q-factors Data Library.

Variables	*LS*	*MKT*	*SMB*	*HML*	*CMA*	*RMW*	*MOM*	HML^{INT}	IA^{HXZ}	ROE^{HXZ}	EG^{HXZ}
LS	1.00										
MKT	-0.26	1.00									
SMB	-0.01	0.26	1.00								
HML	0.12	-0.23	-0.16	1.00							
CMA	0.17	-0.39	-0.13	0.67	1.00						
RMW	0.05	-0.21	-0.45	0.16	0.05	1.00					
MOM	-0.02	-0.16	-0.02	-0.22	-0.01	0.06	1.00				
HML^{INT}	0.11	-0.11	0.00	0.90	0.66	0.17	-0.23	1.00			
IA^{HXZ}	0.15	-0.35	-0.20	0.66	0.91	0.13	0.01	0.64	1.00		
ROE^{HXZ}	-0.04	-0.21	-0.42	-0.11	-0.03	0.65	0.49	-0.13	0.06	1.00	
EG^{HXZ}	0.08	-0.40	-0.40	0.01	0.17	0.42	0.36	-0.06	0.17	0.57	1.00

A.4 Portfolio Returns Relative to Other Models

Table A3: Portfolio returns, other models

The Table presents risk-adjusted annualized ($\times 12$) monthly returns for 5 equally-weighted portfolios of Ad-Capex ratios and for the long-short portfolio (High − Low) with respect to intangibles adjusted model by Eisfeldt et al. (2022), and q-factor model by Hou et al. (2015, 2021).

Panel A: Eisfeldt et al. (2022) Intangible-adjusted model

Portfolios	Low	2	3	4	High	High-Low
α_{int}	0.24	1.79	3.58	3.83	5.64	5.40
$[t]$	(0.18)	(1.36)	(2.44)	(2.67)	(2.65)	(2.87)
β_{mkt}	1.12	1.07	1.05	1.01	0.95	-0.17
$[t]$	(44.51)	(43.57)	(32.29)	(36.70)	(28.14)	(-5.88)
β_{smb}	0.94	0.86	0.82	0.85	0.99	0.04
$[t]$	(14.55)	(16.23)	(9.93)	(10.28)	(10.27)	(0.84)
β_{hml}^{int}	-0.03	0.06	0.09	0.08	0.05	0.08
$[t]$	(-0.39)	(0.86)	(1.11)	(1.01)	(0.36)	(0.94)
β_{mom}	-0.29	-0.25	-0.29	-0.28	-0.32	-0.02
$[t]$	(-5.23)	(-4.43)	(-3.81)	(-4.52)	(-3.08)	(-0.38)
R^2	0.89	0.89	0.86	0.84	0.80	0.07

Panel B: Hou et al. (2015, 2021) q-factor model

Portfolios	Low	2	3	4	High	High-Low
α_{hxz}	3.70	4.14	5.19	5.35	8.53	4.83
$[t]$	(2.10)	(2.14)	(2.24)	(2.44)	(2.63)	(2.26)
β_{mkt}	1.09	1.06	1.04	1.00	0.93	-0.15
$[t]$	(34.13)	(33.49)	(25.62)	(28.64)	(20.88)	(-4.59)
β_{me}	0.68	0.67	0.65	0.65	0.71	0.03
$[t]$	(9.00	(9.66	(6.84	(6.88	(6.55	(0.48
β_{ia}	-0.16	-0.12	-0.06	-0.04	-0.08	0.09
$[t]$	(-1.30)	(-0.99)	(-0.35)	(-0.31)	(-0.35)	(0.69)
β_{roe}	-0.49	-0.50	-0.47	-0.50	-0.61	-0.12
$[t]$	(-4.42)	(-5.56)	(-3.88)	(-4.74)	(-4.28)	(-1.32)
β_{eg}	-0.14	0.01	-0.01	0.01	-0.07	0.07
$[t]$	(-1.58)	(0.09)	(-0.15)	(0.10)	(-0.57)	(0.72)
R^2	0.88	0.89	0.85	0.83	0.79	0.08

A.5 Pre- and Post- 1994 Sub-samples

In this section, I present the full version of the Table 9, with coefficients for the pre- and post-1994 sub-periods in Tables A4 and A5.

Table A4: Portfolio returns, pre-1994.

Panel A: Returns excess of the 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.93	11.33	12.22	12.24	13.59	3.66
$[t]$	(1.89)	(2.20)	(2.40)	(2.38)	(2.54)	(1.99)
SR	0.13	0.15	0.16	0.17	0.19	0.12

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	2.41	3.97	5.09	5.58	7.32	4.91
$[t]$	(0.97)	(1.57)	(2.16)	(2.12)	(2.53)	(2.52)
β	1.21	1.19	1.15	1.08	1.01	-0.20
$[t]$	(23.69)	(19.60)	(17.84)	(17.53)	(15.03)	(-5.60)
R^2	0.75	0.75	0.73	0.68	0.62	0.13

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	1.38	0.51	0.53	0.31	2.77	1.40
$[t]$	(1.04)	(0.36)	(0.41)	(0.22)	(1.58)	(0.66)
β_{mkt}	1.04	1.06	1.04	0.97	0.89	-0.15
$[t]$	(40.53)	(34.80)	(40.04)	(31.08)	(22.52)	(-3.62)
β_{smb}	0.99	1.01	1.05	1.08	1.12	0.13
$[t]$	(13.13)	(22.34)	(19.83)	(15.32)	(14.72)	(1.95)
β_{hml}	-0.07	0.15	0.22	0.26	0.28	0.34
$[t]$	(-0.89)	(1.45)	(2.98)	(3.41)	(3.08)	(3.66)
β_{rmw}	-0.35	-0.08	0.01	0.06	-0.10	0.24
$[t]$	(-3.58)	(-0.81)	(0.08)	(0.72)	(-1.08)	(2.16)
β_{cma}	-0.04	0.01	0.04	0.09	-0.01	0.03
$[t]$	(-0.36)	(0.05)	(0.40)	(0.81)	(-0.07)	(0.21)
R^2	0.92	0.93	0.93	0.91	0.88	0.24

Table A5: Portfolio returns, post-1994.

Panel A: Returns excess of the 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.11	10.80	12.17	12.05	13.20	4.09
[t]	(1.63)	(2.21)	(2.45)	(2.30)	(2.31)	(1.55)
SR	0.10	0.13	0.15	0.14	0.15	0.11

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	-3.58	-0.99	0.63	0.53	1.63	5.21
[t]	(-1.25)	(-0.41)	(0.25)	(0.19)	(0.45)	(2.01)
β	1.40	1.30	1.27	1.27	1.28	-0.12
[t]	(24.06)	(28.99)	(24.80)	(29.18)	(20.38)	(-3.33)
R^2	0.70	0.71	0.68	0.68	0.59	0.03

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	-0.50	0.66	1.99	1.77	3.55	4.05
[t]	(-0.23)	(0.33)	(0.88)	(0.74)	(1.17)	(1.72)
β_{mkt}	1.16	1.12	1.11	1.11	1.07	-0.09
[t]	(23.47)	(27.18)	(18.59)	(25.19)	(16.53)	(-2.10)
β_{smb}	0.73	0.69	0.66	0.67	0.78	0.05
[t]	(6.95)	(8.25)	(6.17)	(6.31)	(5.77)	(0.58)
β_{hml}	0.23	0.11	0.19	0.11	0.09	-0.15
[t]	(3.20)	(1.59)	(2.67)	(1.56)	(0.93)	(-1.75)
β_{rmw}	-0.36	-0.22	-0.13	-0.12	-0.24	0.12
[t]	(-3.23)	(-2.08)	(-1.23)	(-1.11)	(-1.45)	(0.95)
β_{cma}	-0.22	-0.06	-0.15	-0.11	-0.07	0.16
[t]	(-1.29)	(-0.36)	(-0.79)	(-0.66)	(-0.27)	(0.99)
R^2	0.84	0.84	0.79	0.78	0.73	0.05

A.6 Retail versus Non-Retail Firms

Table A6: Portfolio returns, retail firms

Panel A: Returns excess of the 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	4.14	11.35	11.10	11.96	14.67	10.53
[t]	(0.92)	(2.96)	(2.51)	(2.75)	(3.01)	(2.70)
SR	0.05	0.13	0.11	0.12	0.15	0.13

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	-4.73	2.34	1.72	3.01	5.62	10.36
[t]	(-1.38)	(0.88)	(0.59)	(0.97)	(1.65)	(2.74)
β	1.14	1.16	1.21	1.15	1.16	0.02
[t]	(17.64)	(20.77)	(14.11)	(16.23)	(14.78)	(0.33)
R^2	0.47	0.51	0.47	0.43	0.41	0.00

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	-8.68	-1.49	-3.19	0.78	2.71	11.39
[t]	(-2.86)	(-0.58)	(-1.09)	(0.26)	(0.79)	(2.94)
β_{mkt}	1.06	1.09	1.15	1.02	1.04	-0.02
[t]	(22.24)	(20.04)	(16.31)	(15.69)	(13.00)	(-0.23)
β_{smb}	0.98	0.88	1.00	0.96	1.05	0.08
[t]	(10.13)	(9.51)	(9.41)	(8.94)	(7.77)	(0.68)
β_{hml}	0.26	0.20	0.47	0.50	0.19	-0.08
[t]	(2.42)	(1.93)	(4.12)	(4.35)	(1.07)	(-0.42)
β_{rmw}	0.40	0.41	0.44	0.17	0.15	-0.26
[t]	(3.23)	(2.76)	(3.09)	(1.01)	(0.61)	(-1.54)
β_{cma}	0.01	0.05	-0.03	-0.34	0.08	0.07
[t]	(0.06)	(0.33)	(-0.14)	(-1.64)	(0.27)	(0.24)
R^2	0.59	0.62	0.60	0.56	0.54	0.01

Table A7: Portfolio returns, non-retail firms

The following panels present annualized ($\times 12$) monthly returns, raw and risk-adjusted, in excess of the 30-day Treasury bill rates for five equally weighted portfolios of Ad-Capex ratios for non-retail firms. As in Baker et al. (2023), firms are classified as non-retail firms if their SIC codes do not begin with 5.

Panel A: Returns excess of the 30-day Treasury bill rate

Portfolios	Low	2	3	4	High	High-Low
Excess Returns	9.70	12.09	11.74	12.58	13.05	3.35
[t]	(2.47)	(3.32)	(3.28)	(3.41)	(3.34)	(1.97)
SR	0.11	0.15	0.15	0.16	0.16	0.09

Panel B: CAPM adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α	-0.58	2.20	2.24	3.40	4.11	4.69
[t]	(-0.29)	(1.20)	(1.27)	(1.73)	(1.76)	(2.81)
β	1.32	1.27	1.22	1.18	1.15	-0.17
[t]	(30.55)	(31.71)	(29.93)	(30.07)	(23.25)	(-6.64)
R^2	0.71	0.72	0.70	0.68	0.59	0.07

Panel C: Fama and French (2015) adjusted returns

Portfolios	Low	2	3	4	High	High-Low
α_{ff}	0.50	2.35	2.35	3.18	4.42	3.93
[t]	(0.33)	(1.72)	(1.59)	(2.06)	(2.17)	(2.34)
β_{mkt}	1.13	1.11	1.06	1.03	0.97	-0.16
[t]	(31.25)	(34.27)	(29.43)	(31.72)	(22.30)	(-5.94)
β_{smb}	0.81	0.81	0.81	0.80	0.87	0.06
[t]	(10.18)	(12.79)	(10.52)	(9.70)	(9.23)	(1.09)
β_{hml}	0.18	0.11	0.19	0.16	0.19	0.01
[t]	(2.48)	(1.52)	(3.02)	(2.22)	(2.26)	(0.17)
β_{rmw}	-0.35	-0.27	-0.21	-0.21	-0.33	0.02
[t]	(-2.93)	(-2.70)	(-1.80)	(-1.91)	(-2.20)	(0.17)
β_{cma}	-0.23	-0.05	-0.17	-0.08	-0.12	0.11
[t]	(-1.68)	(-0.37)	(-1.21)	(-0.60)	(-0.60)	(0.87)
R^2	0.86	0.87	0.85	0.83	0.77	0.08

A.7 Matching Vivvix and CRSP-Compustat Datasets

The advertising expenditures data from the Kantar Group – currently provided by its group company Vivvix and formerly named Kantar AdSpender and Advertising Insights – is arguably the most comprehensive source of advertising expenditures data at firm and brand levels. The dataset has been commonly used to study the effects of advertising at brand and firm levels, as well as product market concentration (Benkard et al., 2021). It has also been used to validate firms' reported advertising expenditures.

Because Vivvix has no identifiers, I follow the convention of using a fuzzy match algorithm to connect the firm names in the two datasets as in Liang (2023) and Yin (2022). I first obtain the advertising expenditures data at the *ultimate owner* level from Kantar Vivvix. This gives a list of monthly expenditures at the *ultimate owner* level (firms or organizations). I then match the names of the advertisement owners with names from Compustat and SEC EDGAR's 10-K forms. Using EDGAR names in addition to those from Compustat improves the match rate, as the tracked advertisements are assigned to the owners written on the fine point of the advertisements. These tend to be legal names which correspond more closely with filings on EDGAR. The CIK identifiers from EDGAR names are matched with the CUSIP ids from Compustat using Leo Liu's mapping on his GitHub Page (Liu, 2023).

As a result, I have 5906 unique Compustat firm keys (Compustat item: `GVKEY`) matched to 6073 *ultimate owner* entries in Vivvix.

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