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Construction, Real Uncertainty, and Stock-Level Investment Anomalies

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Abstract

We show that the negative relation between real investments and future stock returns is primarily driven by the subsample of firms building additional capacity. We develop a real options model to rationalize that evidence based on the premise that firms need to learn how to best operate modern capacity vintages, inducing idiosyncratic uncertainty in that capacity's production costs over the learning period. Conversely, the uncertainty lowers the expected return of firms with newly built capacity until it is resolved. Further evidence based on profit sensitivities to aggregate conditions; analyst forecast-error volatilities; and high- versus low-tech industry subsamples supports our uncertainty explanation.

I. Introduction

Many empirical studies find that high real-investment stocks tend to yield lower future returns than low investment stocks, with the difference, however, disappearing some years after the investments ("investment anomaly"; see Titman, Wei, and Xie (2004), Anderson and Garcia-Feijóo (2006), Fama and French (2006), (2008), Cooper, Gulen, and Schill (2008), Xing (2008), and Cooper and Priestley (2011), among others). Spurred by this evidence, several recent linear factor models include an investment factor long low and short high-investment stocks to successfully explain stock returns (see, e.g., Fama and French (2015), (2016), Hou, Xue, and Zhang (2015), and Hou, Mo, Xue, and Zhang (2021)).

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We offer evidence that the investment anomaly is almost entirely driven by the subsample of firms physically building additional production capacity ("constructing firms"). Consistent with the vintage capital literature (see Arrow (1962), Thompson (2010), among others), we develop a real options model to explain that finding based on the idea that constructing firms have to experiment with modern capacity to determine how to optimally operate it ("learning-by-doing"). Yet, since the experimenting generates idiosyncratic variations in the capacity's production costs (see, e.g., Foster and Rosenzweig (1995)), modern capacity is characterized by a high uncertainty over some initial period, dragging down the expected returns of constructing firms until that uncertainty is resolved. We finally present evidence supporting our uncertainty explanation, showing that the profits of firms with newly built capacity are less sensitive to their industries' aggregate conditions; that analysts have a harder time forecasting the earnings of those firms; and that the conditional effect of construction on the investment anomaly is more pronounced in industries exposed to greater technological acceleration.

Our main empirical tests condition the investment anomaly on construction work, separately considering investing firms building some fraction of their additional production capacity and those not doing so. Consistent with our focus on physical capacity, we measure investments as the (scaled) change in gross property, plant, and equipment (PPE) over the fiscal year ending in calendar year $t-1$. Conversely, we use *property, plant, and equipment construction-in-progress* (PPE-CIP) at the end of that fiscal year to identify those investing firms which build at least some fraction of their additional capacity. Using the sample period over which PPE-CIP data are available (1986–2016), we first show that, in line with the literature, our investment proxy is significantly negatively related to future stock returns in the pooled sample. More crucially, we next offer evidence that the investment premium is only significant in the constructing but not the non-constructing stock subsample. Our value-weighted portfolio sorts, for example, suggest that the top-minus-bottom investment decile yields an annualized mean return of −13.09% (t-stat: −3.39) in the positive PPE-CIP subsample but of only −4.12% (t-stat: −1.37) in the 0 PPE-CIP subsample. In the same vein, our Fama–MacBeth (FM) (1973) regressions demonstrate that a 25-percentile rise in PPE-CIP scaled by assets makes the monthly investment premium more negative by about 0.61% (t-stat: −3.19).[1]

In our theoretical work, we study a real options model of a firm facing a stochastic price for its output and owning one option to produce output ("asset-in-place") and another one to buy or build one more option to produce output ("growth option"), where, for simplicity, we interpret the options to produce as factories. Consistent with the vintage capital literature, the crux of our model is that since building will ultimately yield a not-yet-existing factory plausibly embedding the latest technological advances, the firm has to experiment with that factory to learn how to operate it at its lowest achievable cost. Yet, since the recent microeconomic learning literature suggests that learning is an inherently stochastic process

[1]As we discuss in detail later, our Supplementary Material shows that our main empirical results are robust with respect to reasonable variations in our methodology and also emerge using other popular investment proxies. It further suggests that our main empirical results have implications for the investment factor used in recent linear factor models, such as the Fama and French (2015) 5-factor model.

(see, e.g., Herriott, Levinthal, and March (1985)), the experimenting likely induces idiosyncratic uncertainty in the production costs of the factory over some initial period, as in, for example, the target-input models of Wilson (1975), Foster and Rosenzweig (1995), and Conley and Udry (2010). In contrast, the production costs of bought (mature) capacity are not uncertain since that same literature also establishes that learning effects quickly evaporate with accumulated experience.

We next calculate the model-implied effect of buying versus building one more factory on the firm's expected return. In line with our empirical evidence, we find that building has a far stronger negative effect than buying, with the effect, however, reversing over a few years. As the only difference between buying and building in our main calculations is that building (but not buying) ultimately yields a factory with initially uncertain costs, our theoretical evidence must come from the effects of uncertainty on the value and systematic risk of the firms' asset-in-place and growth option. As we reveal, greater uncertainty raises the values of both assets but lowers (does not affect) the systematic risk of the asset-in-place (growth option). The higher value arises because a greater option payoff uncertainty boosts the options' upside more than its downside potential. The lower systematic risk of the asset-in-place arises because the greater uncertainty also lowers the option's dollar sensitivity to the underlying asset ("delta"), and the systematic risk of an option is the (scaled) product of delta and the output price-to-option value ratio.[2] In total, a firm converting its growth option into an asset-in-place with greater payoff uncertainty (i.e., a firm building capacity) thus essentially replaces a constant-risk for a lower-risk option, depressing its expected return until the uncertainty resolves.

In our final empirical tests, we look into several new testable implications of our uncertainty explanation to offer evidence supporting it. To achieve that, we notice that the high uncertainty characterizing newly built capacity according to our explanation is real (in contrast to financial) uncertainty. As a result, we ought to be able to detect it in accounting and analyst data. In agreement, the profits of firms with newly built capacity are less sensitive to their industry conditions than those of their peers over a few years after the capacity's installation but not before or after. In the same vein, analysts find it harder to predict the earnings of firms with newly built capacity than those of their peers over those years but again not before or after. We finally realize that the uncertainty characterizing newly built capacity ought to be higher in industries exposed to greater technological acceleration since newly built capacity plausibly differs more from existing (mature) capacity in such industries. In agreement, the conditioning effect of construction on the investment anomaly is stronger in industries producing more patent citations, exposed to more exogenous R&D, or defined as high-tech by the literature.

We add to a large empirical literature studying stock-level investment anomalies, including the studies cited at the start of the introduction. Neoclassical studies in that literature often claim that the anomalies arise either i) because firms invest

[2]While the positive effect of uncertainty on the options' values aligns with the standard textbook argument that (plain-vanilla) options benefit from idiosyncratic underlying-asset volatility (see, e.g., Hull (2022)), its negative effect on the systematic risk of the asset-in-place conforms with the theoretical and empirical evidence of Galai and Masulis (1976), Johnson (2004), Hu and Jacobs (2020), and Aretz, Lin, and Poon (2023) that a greater idiosyncratic call-payoff volatility lowers the call's systematic risk and thus expected excess return.

more when their costs of capital are lower ("q-theory explanation"; see Zhang (2005), Li and Zhang (2010), and Hou et al. (2015)) or ii) because investing firms convert high-risk growth options into low-risk assets-in-place ("real options explanation"; see Carlson, Fisher, and Giammarino (2006), (2010)). Conversely, behavioral studies typically claim that the anomalies arise because managers often invest into value-destroying projects to build empires and investors only slowly see through these actions (see Jensen (1986), Titman, Wei, and Xie (2004), (2009), (2013)). Alternatively, these studies sometimes claim that managers tend to issue shares when their stock is overvalued and use the proceeds to invest (see Baker, Stein, and Wurgler (2003), Polk and Sapienza (2009)). While the empirical evidence on those explanations is mixed (see, e.g., Lam and Wei (2011), Lam, Li, Prombutr, and Wei (2020)), the behavioral has an edge because it can explain why investing stocks tend to yield only temporarily lower returns. We add to those studies by offering a new real-options-based explanation of investment anomalies not only consistent with our new stylized facts but also those in the literature.

We also relate to a literature studying the links between uncertainty and expected stock returns. Using a partial equilibrium model in which investors observe the true asset value of a levered firm only with an additive noise term, Johnson (2004) shows that greater uncertainty about true value leads to a lower expected stock return. While we rely on a similar mechanism, our model features real (and not financial) uncertainty. Using a general equilibrium model in which the true profitability of innovative capacity is exogenous but unobservable, Pastor and Veronesi (2009) reveal that optimal experimenting with the capacity to learn about its true profitability can lead to its wide-spread adoption, raising its systematic risk. Using a general equilibrium model in which young firms learn only slowly about their true exposures to common shocks, Ai, Croce, Diercks, and Li (2018) document that the uncertainty about exposures makes those firms less able to optimally react to shocks, lowering their systematic risk. While these studies assume that uncertainty arises from imprecise knowledge about parameter values, we assume that it arises from the firm experimenting with modern capacity to find out how to best operate that capacity, more directly linking uncertainty and real outcomes.

We finally also add to the real options asset pricing literature. In particular, our real options model is similar to those of Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006) insofar as it also features operating leverage arising from production costs and limits to growth.[3] Adding disinvestment options, it would also be similar to the models of Hackbarth and Johnson (2015) and Aretz and Pope (2018). We abstract from disinvestment options since they have virtually no effect on the expected returns of firms close to exercising their growth options, which are our exclusive focus. Conversely, our model differs from those of Ai and Kiku (2013) and Kogan and Papanikolaou (2013), (2014) insofar as we assume constant investment costs, rather than investment costs exogenously or

[3]While Berk, Green, and Naik (1999) and Gomes, Kogan, and Zhang (2003) are the genesis of the real options asset pricing literature, their models are so-called discount-rate-shock models. In comparison, our model is a cash-flow-shock model, consistent with the models developed in the studies cited in this sentence and the next.

endogenously related to the economic state.[4] Innovating upon all those models, we allow for temporarily uncertain production costs of newly built capacity in our model, using the vintage capital as well as microeconomic learning literatures as foundations for that choice. We then establish that it is that feature of our model (and not those it shares with other models) enabling it to reproduce the investment anomaly.

We proceed as follows: In Section II, we offer our main empirical evidence. In Section III, we develop a real options model of the firm rationalizing that evidence. In Section IV, we empirically assess the model's new implications. Section V concludes. We relay theoretical proofs plus supplementary theoretical and empirical evidence to the Supplementary Material.

II. The Pricing of Investment and Construction

In this section, we offer our main empirical evidence. To do so, we first introduce our main analysis variables. We next study the investment anomaly both in the full sample and the subsamples of firms physically building or not building additional capacity. We finally qualitatively discuss the results from robustness and supplementary tests, offering the details in our Supplementary Material. We review our control variables, data sources, and sample construction and winsorization techniques, concisely summarize our analysis variable definitions (see Table A1), and give descriptive statistics (see Table A2) in Appendix A.

The key takeaways from our main empirical tests are that while the investment anomaly still exists in our full sample, it is almost exclusively driven by the subsample of firms physically building additional capacity. Notwithstanding, the anomaly also dissipates in that subsample about 4–5 years after the firms' investments into additional capacity.

A. Main Analysis Variables

In line with our focus on investments into physical production capacity, we measure a firm's investment activity as the change in its gross PPE over the fiscal year ending in calendar year $t-1$ scaled by its assets at the start of that fiscal year (INVESTMENT). We then use the calculated value from June of calendar year t to May of calendar year $t+1$. Different from CAPEX-based proxies, such as Titman et al.'s (2004) abnormal CAPEX or Xing's (2008) CAPEX-to-PPE, INVESTMENT also captures physical capacity expansions originating from acquisitions. Different from broader proxies, such as Cooper et al.'s (2008) asset growth, it, however, excludes investments into non-productive (physical or intangible) assets, such as cash, cash equivalents, and account receivables (see Peters and Taylor (2017)).

[4]The upshot is that growth options are riskier than assets-in-place in our model. Thus, if growth firms simply held more growth options than value firms, our model would not explain the value premium. Yet, if they also held more newly built assets-in-place (i.e., not-long-ago-exercised options), it could explain the value premium. Despite that, given the temporary nature of the uncertainty in production costs, our model would only ever produce a temporary but not a persistent value premium.

We rely on a firm's PPE-CIP account balance (Compustat item: fatc) at the end of the fiscal year in calendar year $t-1$ to find out whether some of the firm's investments resulted in it physically building additional capacity. As mandated by U.S. accounting rules, firms have to collect expenses incurred in the construction of an asset (as, e.g., material costs, vendor invoices, and transportation expenses) in the PPE-CIP account over the construction period. When construction finishes, they have to transfer the account balance into the appropriate fixed-PPE account, often "buildings" or "machinery and equipment." Since firms with a positive PPE-CIP balance must necessarily have outstanding construction work, we often choose them as our "constructing firms," identifying those firms using a dummy variable equal to 1 for them and else 0 (DUMMY_CONSTRUCTION). To be more granular, we however also look into a firm's construction intensity, defined as the PPE-CIP balance at the end of the fiscal year in calendar year $t-1$ scaled by assets at the start of that fiscal year (CONSTRUCTION).

We acknowledge that our strategy to identify constructing firms based on PPE-CIP data is imperfect. While a greater amount of capacity-under-construction raises both gross PPE (and thus INVESTMENT) and PPE-CIP, we only observe the PPE-CIP balance at the end of a fiscal year. The upshot is that we do not capture construction expenses arising from projects started either before or within the fiscal year ending in calendar year $t-1$ and finished within that year.[5] An additional upshot is that the PPE-CIP balance at the end of that same fiscal year may include construction expenses not incurred over that year (and thus the period over which we compute INVESTMENT) but over earlier years. Notwithstanding, the PPE-CIP data still allow us to capture most larger-scale construction projects since, for example, the construction of a production factory takes, on average, about 2 years (see, e.g., Koeva (2000)).

B. The Pricing of INVESTMENT

We next rely on portfolio sorts to study whether, in accordance with the literature, INVESTMENT is significantly negatively related to future stock returns over our sample period. At the end of each June in calendar year t, we thus sort our sample firms into portfolios according to the 10th, 50th, and 90th percentiles of the INVESTMENT distribution on that date, focusing on these percentiles to contrast firms making substantial investments into their PPE with those making close-to-no such investments. We also create a spread portfolio long the top and short the bottom INVESTMENT portfolio ("LS90–10"). We value or equally weight the portfolios and hold them from start of July of calendar year t to end of June of calendar year $t+1$. We risk-adjust portfolio returns by regressing them on either Fama and French's (2015) 5-factor-model or Hou et al.'s (2015) q-theory factors and reporting the regression intercept ("alpha"). In either case, we however omit the investment factor (labeled CMA or IA) from the other factors since its inclusion would explain the spread portfolio return almost by construction.

[5]To partially address this issue, we later also choose as constructing firms those with a positive PPE-CIP balance at the start *or* end of the fiscal year ending in calendar year $t-1$.

TABLE 1

Univariate Investment Portfolios

Table 1 presents the results of portfolios univariately sorted on INVESTMENT. At the end of June of each calendar year t, we sort stocks into portfolios according to the 10th, 50th, and 90th percentiles of the INVESTMENT distribution at the end of that month. We value (Panel A) or equally (Panel B) weight the portfolios and hold them from start-July of year t to end-June of year $t+1$. We also form a spread portfolio long the top and short the bottom portfolio ("LS90–10"). Columns 1–3 report the mean number of stocks and the time-series means of the value (Panel A) or equal (Panel B) weighted cross-sectional means of INVESTMENT and CONSTRUCTION per portfolio, respectively. The plain numbers in columns 4–6 are, respectively, the mean excess returns and alphas of the q-theory and 5-factor (FF5) model (excluding their investment factors), annualized and in percentage. The numbers in square brackets in those same columns are Newey and West (1987) t-statistics with a 6-month lag length. See Table A1 in Appendix A for more details about variable definitions.

	Mean # Stocks	Mean INVESTMENT	Mean CONSTRUCTION	Mean Excess Return	q-Theory Model Alpha	FF5 Model Alpha
	1	2	3	4	5	6
Panel A. Value-Weighted Portfolios						
00–10	162	0.55	0.72	9.57	1.47	0.06
10–50	649	2.95	1.22	8.33	0.59	0.42
50–90	649	9.36	2.01	8.01	0.94	1.30
90–100	162	44.41	2.80	3.50	−3.91	−5.51
LS90–10				−6.07	−5.38	−5.57
t-stat				[−2.27]	[−2.26]	[−2.22]
Panel B. Equal-Weighted Portfolios						
00–10	162	0.55	0.46	11.19	4.35	1.18
10–50	649	2.88	0.84	10.86	3.67	1.15
50–90	649	9.81	2.08	9.74	2.36	−0.04
90–100	162	47.08	5.47	3.60	−3.41	−7.20
LS90–10				−7.59	−7.76	−8.38
t-stat				[−3.04]	[−3.45]	[−3.64]

Table 1 presents the portfolio sort results, showing the annualized mean excess returns and alphas of the value (Panel A) and equal (Panel B) weighted portfolios (in %) plus several portfolio characteristics. The portfolio characteristics include the average number of stocks and the average cross-sectional means of INVESTMENT and CONSTRUCTION over our sample period. The table further reports Newey and West (1987) t-statistics calculated with a 6-month lag length for the spread portfolio returns and alphas (in square brackets). In line with the literature, the table shows that INVESTMENT commands a significant negative premium. Considering the value-weighted portfolios, column 4 suggests that the mean excess return drops from 9.57% per annum for the bottom INVESTMENT decile to 3.50% for the top (see Panel A). The spread is a significant −6.07% (t-stat: −2.27). Turning to the equal-weighted portfolios, we find an even stronger negative relation, with the spread over them being a significant −7.59% (t-stat: −3.04; Panel B). Unsurprisingly, columns 5 and 6 reveal that correcting for either set of benchmark factors hardly affects the mean spread portfolio returns in Panels A and B.

In line with our expectations, column 2 of Table 1 confirms that while the bottom decile firms hardly raise their PPE in the average year, the top decile firms raise it by a substantial value-weighted 44% and equal-weighted 47% of their assets. Consistent with the positive correlation between INVESTMENT and CONSTRUCTION shown in Table A2 in Appendix A, column 3 demonstrates that while the bottom decile firms have less than 1% of their assets under construction, the corresponding number for the top decile firms is a value-weighted 3% and an equal-weighted 5%. Finally, column 1 reassures us that all portfolios univariately sorted on INVESTMENT contain enough stocks to be well-diversified.

C. The Conditional Effect of CONSTRUCTION

We now present our main empirical result, showing that the negative premium of INVESTMENT is almost exclusively attributable to firms physically building some fraction of their additional capacity. At the end of each June in calendar year *t*, we thus again sort our sample firms into portfolios according to the 10th, 50th, and 90th percentiles of the INVESTMENT distribution on that date. We next, however, also sort them into portfolios based on whether DUMMY_CONSTRUCTION takes on a value of 0 or 1. We finally create double-sorted portfolios from the intersection of the two univariate sorts. Within each DUMMY_CONSTRUCTION portfolio, we also form a spread portfolio long the top and short the bottom INVESTMENT portfolio ("LS90–10"). We finally create double-spread portfolios long the univariate spread portfolio formed from positive PPE-CIP stocks (DUMMY_CONSTRUCTION = 1) and short that formed from 0 PPE-CIP stocks (DUMMY_CONSTRUCTION = 0). We again value or equally weight the portfolios, hold them from July of calendar year t to June of calendar year $t+1$, and risk-adjust their mean returns using the same factors as before.

Using the same columns as Table 1, Table 2 offers the value (Panel A) and equal (Panel B) weighted double portfolio sort results. While the first (second) subpanel in each main panel focuses on the positive (0) PPE-CIP stock portfolios, the final subpanel concentrates on the double-spread portfolios. The table reports that the investment anomaly is almost entirely driven by firms with positive PPE-CIP values (i.e., constructing firms). The value-weighted portfolios in Panel A, for example, establish that while the INVESTMENT spread portfolio formed from constructing firms yields a significant mean excess return of −13.09% per annum (*t*-stat: −3.39), the corresponding number for the spread portfolio formed from non-constructing firms is an only insignificant −4.12% (*t*-stat: −1.37; see column 4). The spread in those numbers is a significant −8.97% (*t*-stat: −2.09). The equal-weighted portfolios in Panel B yield similar conclusions. As before, columns 5 and 6 demonstrate that adjusting for either set of benchmark factors again only marginally affects our main conclusions. Interestingly, columns 2 and 3 finally reveal that PPE-CIP accounts for an economically meaningful 25% of the PPE changes of top-decile firms with positive PPE-CIP values in both panels.[6]

Figure 1 analyzes the economic significance of our double portfolio sort results, plotting the cumulative returns of value (Graph A) and equal (Graph B) weighted spread portfolios long the *bottom* INVESTMENT decile and short the top formed from either all stocks, constructing stocks, or non-constructing stocks over our sample period. The figure reveals that the spread portfolio formed from

[6]Surprisingly, the bottom INVESTMENT decile firms in Panels A and B yield higher mean CONSTRUCTION than INVESTMENT values. Since new construction (i.e., PPE-CIP) expenses raise gross PPE and, in turn, INVESTMENT, the inference is that those firms must still be engaged in construction projects started before the fiscal year ending in calendar year $t-1$, in line with some construction projects taking a long time to complete.

TABLE 2

Portfolios Double-Sorted on Investment and Construction

Table 2 presents the results from portfolios double-sorted on INVESTMENT and DUMMY_CONSTRUCTION. At the end of June of each calendar year *t*, we sort stocks into portfolios according to the 10th, 50th, and 90th percentiles of the INVESTMENT distribution at the end of that month. We independently sort them into portfolios according to whether DUMMY_CONSTRUCTION is 0 or 1 at the same time. The intersection of the two sets gives us the double-sorted portfolios. We value (Panel A) or equally (Panel B) weight the portfolios and hold them from start-July of year *t* to end-June of year $t+1$. We report the DUMMY_CONSTRUCTION = 1 (0) portfolio results in the first (second) subpanel of each panel. Within each DUMMY_CONSTRUCTION portfolio, we further form a spread portfolio long the top and short the bottom investment portfolio ("LS90–10"). We finally form a spread portfolio long the investment spread portfolio formed from DUMMY_CONSTRUCTION = 1 and short that formed from DUMMY_CONSTRUCTION = 0 stocks (see third subpanels). Columns 1–3 report the mean number of stocks and the time-series means of the value (Panel A) or equal (Panel B) weighted cross-sectional means of INVESTMENT and CONSTRUCTION per portfolio. The plain numbers in columns 4–6 are, respectively, the mean excess returns and alphas of the *q*-theory and 5-factor (FF5) model (excluding their investment factors), annualized and in percentage. The numbers in square brackets in those columns are Newey and West (1987) *t*-statistics with a 6-month lag length. See Table A1 in Appendix A for more details about variable definitions.

	Mean # Stocks	Mean INVESTMENT	Mean CONSTRUCTION	Mean Excess Return	*q*-Theory Model Alpha	FF5 Model Alpha
	1	2	3	4	5	6
Panel A. Value-Weighted Portfolios						
Panel A.1: Constructing Stocks						
00–10	41	0.54	2.04	11.99	3.49	2.05
10–50	229	3.05	2.82	8.05	−0.05	−0.45
50–90	272	9.33	4.75	9.03	1.69	2.28
90–100	58	37.95	9.23	−1.10	−7.51	−6.75
LS90–10 (1)				−13.09	−11.01	−8.80
t-stat				[−3.39]	[−3.13]	[−2.75]
Panel A.2: Non-Constructing Stocks						
00–10	121	0.55	0.00	9.49	1.50	0.04
10–50	420	2.87	0.00	8.84	1.21	1.11
50–90	377	9.40	0.00	7.27	0.33	0.50
90–100	105	45.87	0.00	5.37	−1.84	−4.68
LS90–10 (2)				−4.12	−3.34	−4.72
t-stat				[−1.37]	[−1.19]	[−1.57]
Panel A.3: Difference						
Diff. (1)–(2)				−8.97	−7.66	−4.08
t-stat				[−2.09]	[−1.79]	[−0.98]
Panel B. Equal-Weighted Portfolios						
Panel B.1: Constructing Stocks						
00–10	41	0.56	1.34	14.17	6.85	3.42
10–50	229	3.00	1.95	11.22	3.87	1.10
50–90	272	9.92	3.98	10.29	2.90	0.05
90–100	58	39.29	9.40	1.37	−5.84	−8.66
LS90–10 (1)				−12.80	−12.69	−12.08
t-stat				[−5.75]	[−5.86]	[−6.39]
Panel B.2: Non-Constructing Stocks						
00–10	121	0.55	0.00	10.29	3.63	0.55
10–50	420	2.83	0.00	10.50	3.38	0.93
50–90	377	9.76	0.00	9.41	2.08	−0.02
90–100	105	51.10	0.00	5.01	−1.77	−6.16
LS90–10 (2)				−5.28	−5.40	−6.71
t-stat				[−1.65]	[−1.81]	[−2.19]
Panel B.3: Difference						
Diff. (1)–(2)				−7.52	−7.29	−5.37
t-stat				[−2.53]	[−2.30]	[−1.77]

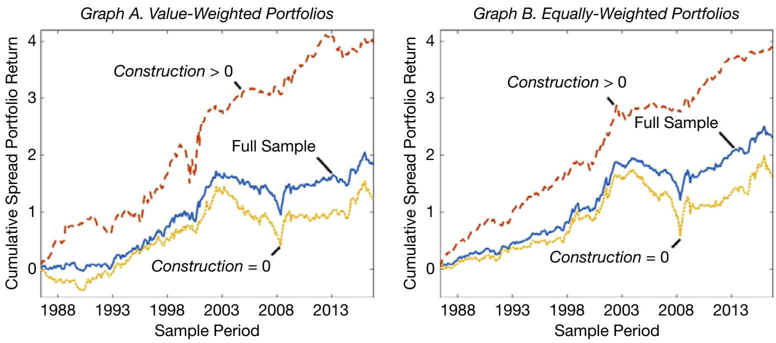
constructing stocks is markedly more profitable than that formed from non-constructing stocks (e.g., value-weighted excess payoff: about $4 vs. about $1).

In Table 3, we switch to FM regressions to verify that our evidence is robust to variations in methodology and to more granularly conditioning on construction.

FIGURE 1

The Cumulative Returns of Investment Spread Portfolios Formed from All, Constructing, and Non-Constructing Stocks

In Figure 1, we plot the cumulative returns of value (Graph A) and equal (Graph B) weighted spread portfolios long the bottom INVESTMENT decile and short the top decile over our sample period. The spread portfolios are formed from either all firms (solid blue line), only constructing firms (dashed red line), or only non-constructing firms (dotted yellow line).



In column 1, we regress single-stock returns over month t on INVESTMENT and our controls measured until the start of that month to confirm that we also find an investment anomaly in our regressions. More importantly, columns 2 and 3 add interactions between INVESTMENT and either CONSTRUCTION or a CONSTRUCTION rank variable and the CONSTRUCTION variable itself. While the interaction with CONSTRUCTION directly conditions the INVESTMENT anomaly on a firm's construction intensity, its effect may be unduly distorted by outliers. To guard against outliers, we also use the alternative interaction. In columns 4 and 5, we finally separately run the regression in column 1 on positive (DUMMY_CONSTRUCTION = 1) or 0 (DUMMY_CONSTRUCTION = 0) PPE-CIP stocks, reporting the differences in estimates in column 6. While the plain numbers are monthly premium estimates (in %), those in square brackets are Newey and West (1987) t-statistics with a 6-month lag length.

The FM regressions yield results in accordance with the portfolio sorts. To be specific, column 1 of Table 3 shows that the INVESTMENT premium remains significantly negative (estimate: −1.19% per month; t-stat: −3.23) even after accounting for MARKET_BETA, MARKET_SIZE, BOOK_TO_MARKET, MOMENTUM, and PROFITABILITY effects in stock returns. More noteworthily, columns 2 and 3 demonstrate that the premium crucially depends on the extent to which firms build additional capacity. Column 3, e.g., reveals that a 25-percentile rise in CONSTRUCTION makes the premium more negative by about 0.61% per month (t-stat: −3.19). In complete agreement, the subsample regressions in columns 4 and 5 establish that the INVESTMENT premium is a highly significant −2.51% per month (t-stat: −6.94) in the positive PPE-CIP subsample but an only insignificant −0.61% (t-stat: −1.56) in the 0 PPE-CIP subsample, with the difference equal to a highly significant −1.90% (t-stat: −4.20; see column 4−5).

Given the well-known evidence that the negative full-sample investment premium emerges only over a short period after the investments (see Titman et al. (2004)), a final question is whether the corresponding premium in constructing

TABLE 3

Regressions of Stock Returns on Investment Interacted with Construction

Table 3 presents the results from Fama and MacBeth (1973) regressions of single-stock returns over month t on combinations of investment, construction, and controls measured until the end of month $t-1$. In columns 1–3, we report the results from full-sample regressions on, respectively, INVESTMENT and the controls; INVESTMENT, an interaction between INVESTMENT and CONSTRUCTION, CONSTRUCTION, and the controls; and INVESTMENT, an interaction between INVESTMENT and a CONSTRUCTION rank variable, the rank variable, and the controls. In columns 4 and 5, we report the results from subsample regressions run separately on firms with a positive and 0 CONSTRUCTION value, respectively. Column 4–5 finally reports the difference in estimates across the subsample regressions. The plain numbers are monthly premium estimates, in percentage. The numbers in square brackets are Newey and West (1987) t-statistics calculated with a 6-month lag length. See Table A1 in Appendix A for more details about variable definitions.

	All Stocks	All Stocks	All Stocks	Cons. Stocks	Non-Cons. Stocks	Spread
	1	2	3	4	5	4 – 5
INVESTMENT	−1.19	−0.85	−0.80	−2.51	−0.61	−1.90
	[−3.23]	[−2.06]	[−1.82]	[−6.94]	[−1.56]	[−4.20]
INVESTMENT × CONSTRUCTION		−20.97				
		[−2.50]				
CONSTRUCTION		0.47				
		[0.33]				
INVESTMENT × RANK_CONSTRUCTION			−2.43			
			[−3.19]			
RANK_CONSTRUCTION			0.19			
			[2.00]			
MARKET_BETA	−0.00	0.00	0.00	0.02	0.01	0.01
	[−0.01]	[0.00]	[0.01]	[0.08]	[0.04]	[0.09]
MARKET_SIZE	−0.03	−0.03	−0.04	−0.07	−0.02	−0.05
	[−0.70]	[−0.75]	[−0.82]	[−1.56]	[−0.50]	[−1.90]
BOOK_TO_MARKET	0.23	0.22	0.22	0.11	0.27	−0.16
	[2.65]	[2.57]	[2.58]	[0.96]	[3.24]	[−1.79]
MOMENTUM	0.91	0.91	0.91	0.81	0.98	−0.17
	[4.18]	[4.16]	[4.19]	[3.29]	[4.60]	[−1.23]
PROFITABILITY	0.67	0.66	0.67	0.58	0.69	−0.11
	[2.89]	[2.88]	[2.90]	[2.00]	[2.97]	[−0.47]
Constant	0.90	0.90	0.90	1.15	0.82	0.33
	[2.03]	[2.05]	[2.04]	[2.70]	[1.82]	[1.79]

stocks is similarly temporary. To find out, we reestimate the subsample FM regressions in columns 4 and 5 of Table 3, leading, however, the stock return used as regressant by 0–60 months. Plotting the thus calculated INVESTMENT premiums obtained from the constructing and non-constructing firm subsamples in Graphs A and B of Figure 2, the figure vividly suggests that the investment premium also disappears in the subsample of constructing firms after about 4–5 years.[7]

D. Robustness Tests and Further Implications

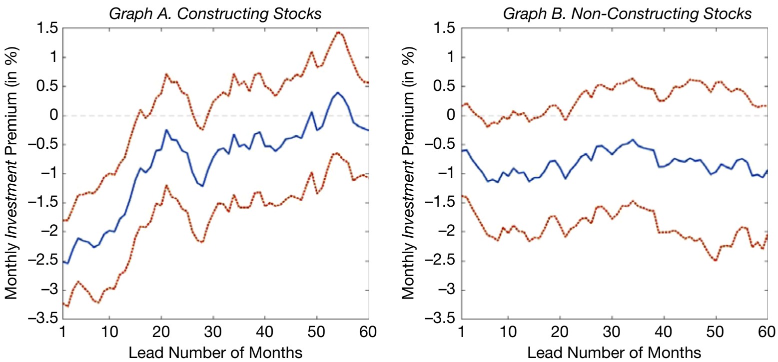
Our Supplementary Material shows that our main evidence is robust with respect to reasonable methodological changes concerning, e.g., the treatment of missing PPE-CIP observations, the definition of constructing firms, and our sales, stock price, and market size filters (see the appendix and the Supplementary Material for more details). In the same Supplementary Material, we further demonstrate that our main evidence is also robust with respect to running weighted least squares (WLS) regressions based on 1-month-lagged market-size or gross-return rather than the ordinary least squares (OLS) regressions in Table 3.

[7]Notice that, even when $x = 0$, the investments occurred already about a year in the past.

FIGURE 2

The INVESTMENT Premium over the Post-Investment Period

In Figure 2, we plot the INVESTMENT premium from FM regressions of single-stock returns over month $t+x$ on INVESTMENT and controls measured until the start of month t, separately estimated on firms with positive (Graph A) and 0 (Graph B) PPE-CIP values (see columns 4 and 5 in Table 3). We let x vary from 0 to 60 months in increments of 1. Solid lines are monthly INVESTMENT premium estimates (in %), while dotted lines are 95% confidence bands calculated from Newey and West (1987) standard errors with a 6-month lag length.



Turning to broader implications, our Supplementary Material establishes that our main evidence also emerges using alternative popular investment proxies, such as i) CAPEX-to-PPE (Xing (2008)); ii) abnormal CAPEX-to-sales (Titman et al. (2004)); iii) capital growth (Peters and Taylor (2017)); and iv) asset growth (Cooper et al. (2008)). In line with expectations, our evidence however becomes weaker the less a proxy reflects investments into physical productive capacity. The same material finally documents that Fama and French's (2015) CMA benchmark factor formed from constructing firms significantly outperforms the original factor and the factor formed from non-constructing firms, and that only the constructing-firm factor (but not its counterpart) prices the original factor in spanning tests.

Taken together, this section suggests that the investment anomaly is almost entirely driven by firms physically building additional capacity. Notwithstanding, the anomaly also disappears in that subsample of firms about 4–5 years after the investments.

III. A Real Options Model with Newly Built Capacity

In this section, we develop a real options model of the firm to rationalize our empirical evidence in Section II. We first discuss the microeconomic foundations of our model. We next outline its assumptions and solution. We finally study the value and systematic risk implications of buying versus building capacity and then directly compute the model-implied effect of an output-price-induced real investment on the firm's expected excess return.

A. The Microeconomic Foundations of Our Model

We start from the insight that firms physically building additional production capacity will ultimately obtain not-yet-existing capacity plausibly embedding the most recent technological advances. In line with the vintage capital literature (see, e.g., Arrow (1962), Solow (1997), and Thompson (2010)), we reason that firms have to experiment with (i.e., operate) that capacity to determine how to minimize its production costs and to realize its full potential ("learning-by-doing"). Borrowing from the recent microeconomic learning literature, we conjecture that learning-by-doing is an inherently stochastic process (Herriott et al. (1985)). In particular, the so-called target-input models in that literature conjecture that while firms know the minimum feasible cost at which modern capacity can be operated, they have to rely on trial-and-error methods to find the optimal combination of inputs necessary to achieve that cost (see Wilson (1975), Foster and Rosenzweig (1995), and Conley and Udry (2010)).[8] At the start of each period, firms thus use their current best-guess of that combination to produce output, observe the resulting costs over the period, and update their current best-guess at the end of the period. We highlight four important implications of target-input models for our modeling choices:

1. While firms learn about modern capacity, the production costs of that capacity are not only higher but also more uncertain than those of equivalent mature capacity.
2. Since learning is unlikely to be related to the economic state, the uncertainty in the initial production costs of modern capacity is plausibly idiosyncratic.
3. The effects of learning quickly evaporate with accumulated experience, so that only the initial (but not later) production costs of newly built capacity are uncertain.
4. For the same reason, learning matters only for modern but not mature capacity.

In the following subsections, we work these implications into a standard real options model of the firm, to find out whether stochastic learning about how to best operate modern capacity helps us to shed more light on our empirical evidence in Section II.[9]

B. Modeling Assumptions

We consider an all-equity-financed firm operating in continuous time $t \in [0, +\infty]$ and owning one option to produce a unique output good ("asset-in-place") and one option to buy or build another option to produce the same output good ("growth option").[10] For simplicity, we interpret the options to produce as factories, index them by $k \in \{1,2\}$, where $k=1$ (2) denotes the installed (not-yet-installed) factory, and assume that the installed factory is "mature" (to be clarified later). Further assuming that the firm can costlessly and instantaneously switch on

[8] Jovanovic and Nyarko (1995), (1996) and Karp and Lee (2001) rely on similar stochastic learning models.

[9] We are not the first to study how learning affects asset prices. To wit, Ai, Croce, and Li (2013) and Ai, Croce, Diercks, and Li (2018) also assume that firms only slowly learn about the functionality of modern capacity, inducing them to initially make suboptimal real decisions lowering their systematic risk (see also Li, Tsou, and Xu (2023)).

[10] In a prior version of our article, we awarded the firm a finite number of assets-in-place and an infinite number of growth options, eliminating the "limits to growth" implicit in the current version. Doing so, our model produced insights in broad agreement with those obtained from the model in the current version.

and off the installed factory, the switched-on factory produces one output good unit per time unit at the constant variable cost C_1. Conversely, the firm instantaneously sells all produced output at the stochastic price θ obeying the geometric Brownian motion (GBM):

$$d\theta = \alpha\theta dt + \sigma\theta dW, \tag{1}$$

where α and σ are, respectively, the constant output-price drift rate and volatility, and W is a Brownian motion. Assuming that the firm switches on (off) the installed factory in some instant, its total profits per time unit are: $\Pi = \theta - C_1$ ($\Pi = 0$), so that the firm maximizes its value by switching on the installed factory in that instant if and only if $\theta \geq C_1$.

In each instant, the firm can spend the constant I to exercise the growth option and to buy or build the underlying factory. We abstract from choice, so that the firm either always buys or always builds. If the firm buys the factory, it obtains a mature factory able to produce one more output good unit per time unit at a constant cost of C_2, where $C_2 > C_1$. Conversely, if the firm builds the factory, it initially has to experiment with the factory to learn how to best operate it. To be specific, we assume that the firm uses trial-and-error methods to find the combination of inputs necessary to achieve the lowest feasible cost, inducing the cost of the factory to not only be higher than that of the mature factory but also uncertain (see Section III.A). In line with evidence that mature and newly built factories tend to be similarly productive (see, e.g., Jensen, McGuckin, and Stiroh (2001)), we next, however, also posit that newly built factories save on "repair, maintenance, and upgrading costs" incurred by mature factories to be able to compete.

More rigorously, let us denote the initial cost of the newly built factory by C_2^t and relate its log value, $c_2^t \equiv \ln\left(C_2^t\right)$, to the log cost of mature capacity, $c_2 \equiv \ln(C_2)$, by

$$c_2^t = c_2 - m + l + \varepsilon, \tag{2}$$

where $m > 0$ are the constant repair, maintenance, and upgrading costs incurred by the mature factory to stay competitive (the advantage of building) and $l + \varepsilon$ the excess costs incurred by the newly built factory due to the firm still learning how to best operate that factory, with $l > 0$ a constant and ε a mean-zero normal error with variance $\sigma^2_{c_2^t}$ (the disadvantage).[11] We then ensure that the mature and newly built factory tend to be similarly productive by setting $m = l$. We finally assume that the newly built factory matures (i.e., that its log production cost becomes equal to c_2) according to a Poisson process with a constant intensity parameter λ.

We conjecture that, before the installation of the newly built factory, the firm and stock investors know the variance but not the realization of the uncertain component of the cost due to the firm still learning about the factory, ε. To keep the mathematics tractable, we, however, assume that, immediately after installation,

[11]While target-input models imply that the costs of a newly built factory take on multiple uncertain values above the lowest feasible cost during the period over which the firm experiments with the factory, we rely on just one single value to be able to solve our model in quasi-closed-form.

the firm learns about the realization. In contrast, investors never learn about it as they do not observe the firm's operating decisions and the firm cannot communicate its knowledge to them. Notwithstanding, the firm is able to signal to investors (through, e.g., its financial reports) once it has finished learning about the newly built factory and can operate that factory at the no-longer-uncertain log costs of c_2.[12]

Assuming a complete market without arbitrage chances, the first two fundamental theorems of asset pricing imply the existence of a unique stochastic discount factor, Λ, which prices all assets by construction. We posit that the differential of that factor obeys the GBM:

$$d\Lambda = -r\Lambda dt + \sigma_\Lambda \Lambda dW^{(\Lambda)}, \tag{3}$$

where r is the constant risk-free rate of return, σ_Λ is the constant volatility of the stochastic discount factor, and $W^{(\Lambda)}$ is a Brownian motion. We further conjecture that $dWdW^{(\Lambda)} = \rho dt$, where ρ is the constant instantaneous correlation between the output price θ and the stochastic discount factor Λ and determines the risk premium of a mimicking portfolio perfectly positively correlated with θ. To be more specific, the expected excess return of that portfolio is $\mu - r = -\text{cov}(d\theta/\theta, d\Lambda/\Lambda)/dt = -\rho\sigma\sigma_\Lambda$. In line with Section III.A, we finally assume that the excess cost of newly built capacity due to learning-by-doing effects, ε, is independent of the stochastic discount factor since learning is unlikely to be related to the economic state.[13]

C. Model Solution

In our model, the firm is a portfolio of options to produce or to buy or build more options to produce. The upshot is that the firm's value is the sum taken over the option values and that its expected excess return is, consistent with portfolio theory, a value-weighted average of the expected excess option returns. In the Supplementary Material, we show that the expected (instantaneous) excess return of each option, $E[R_O] - r$, is

$$E[R_O] - r = V_\theta(\theta/V)(\mu - r), \tag{4}$$

where V is the option value and V_θ the first partial derivative of option value with respect to the output price θ. Viewing $V_\theta(\theta/V)$ as the option's "elasticity," we notice that, since $\mu - r$ is constant, it is variations in that elasticity which drive variations in $E[R_O] - r$.

Following standard techniques (see Dixit and Pindyck (1994)), our Supplementary Material shows that the value of the mature factory indexed by k, V_k^m, is

[12] We stress that the difference in the firm's and investors' information sets is important since it is investors who value the firm. The upshot is that investors still consider uncertainty in the initial costs of a newly built factory even after the firm owns the factory and can observe those costs.

[13] While it may be surprising that we abstract from the time necessary to build factories, we do so since prior studies often find that time-to-build has only marginal asset pricing implications (see, e.g., Carlson et al. (2010)). In agreement with that conclusion, our Supplementary Material confirms that an extended version of our model with time-to-build yields results identical to those extracted from our main model.

$$V_k^m = \begin{cases} A_1\theta^{\beta_2} + \frac{\theta}{\delta} - \frac{C_k}{r}, & \text{if} \quad \theta \geq C_k, \\ A_2\theta^{\beta_1}, & \text{if} \quad \theta < C_k, \end{cases} \tag{5}$$

where β_1, β_2, A_1, and A_2 are parameters defined in that material, and $\delta \equiv \mu - \alpha$. While $A_2\theta^{\beta_1}$ and $A_1\theta^{\beta_2}$ are the values of the real options to switch on and off the factory, respectively, $\theta/\delta - C_k/r$ is the value obtained from perpetually using the factory.

We offer the value of a newly built factory in the following proposition:

Proposition 1. The value of a newly built factory able to produce one output good unit per time unit at an uncertain log variable cost of $c_2^t = c_2 + \mu_{c_2^t} + \varepsilon$, where $\varepsilon \sim N\left[0, \sigma_{c_2^t}^2\right]$, over a length of time obeying a Poisson process with constant intensity parameter λ and a constant log variable cost of c_2 after that period, V_2^{nb}, is

$$V_2^{nb} = \begin{cases} P_{\{C_2^t \geq \theta\}}\left(E_1[B_2]\theta^{\beta_1'} + B_3\theta^{\beta_2'} - \frac{\theta}{\delta+\lambda}\right) + P_{\{\theta > C_2^t \geq C_2\}}\left(E_2[B_1]\theta^{\beta_2'} - \frac{E_2\left[C_2^t\right]}{r+\lambda}\right) \\ +P_{\{C_2^t < C_2\}}\left(E_3[D_1]\theta^{\beta_2'} - \frac{E_3\left[C_2^t\right]}{r+\lambda}\right) + A_1\theta^{\beta_2} + \frac{\theta}{\delta} - \frac{C_2}{r} + \frac{C_2}{r+\lambda}, & \textit{if } \theta \geq C_2, \\ P_{\{C_2^t \geq C_2\}}E_4[B_4]\theta^{\beta_1'} + P_{\{C_2 > C_2^t \geq \theta\}}E_5[D_4]\theta^{\beta_1'} \\ +P_{\{C_2^t < \theta\}}\left(D_2\theta^{\beta_1'} + E_6[D_3]\theta^{\beta_2'} + \frac{\theta}{\delta+\lambda} - \frac{E_6\left[C_2^t\right]}{r+\lambda}\right) + A_2\theta^{\beta_1}, & \textit{if } \theta < C_2, \end{cases} \tag{6}$$

where A_1, A_2, B_1 to B_4, D_1 to D_4, β_1, β_2, β_1', and β_2' are parameters, $P_{\{C_2^t \geq \theta\}}$, $P_{\{\theta > C_2^t \geq C_2\}}$, $P_{\{C_2^t < C_2\}}$, $P_{\{C_2^t \geq C_2\}}$, $P_{\{C_2 > C_2^t \geq \theta\}}$, and $P_{\{C_2^t < \theta\}}$ are probabilities, and $E_1[.]$ to $E_6[.]$ are conditional expectations. We state the definitions of the parameters and give the closed-form solutions for both the probabilities and the conditional expectations in the Supplementary Material.

Proof. See the Supplementary Material.[14]

We can derive equation (6) by recognizing that, conditional on the uncertain initial variable cost C_2^t, the newly built factory is equivalent to a no-cost-uncertainty factory able to produce one output unit per time unit at a constant cost of C_2^t over an initial period with a random length and at a constant cost of C_2 afterward. After valuing the no-cost-uncertainty factory, we can then simply integrate its closed-form solution over the distribution of C_2^t to obtain the closed-form solution for the value of the newly built factory with uncertainty.

Using more standard techniques again, our Supplementary Material finally reveals that the value of the growth option on the second factory, G_2, is

[14]We note that the $\mu_{c_2^t} \equiv -m + l$ parameter in the proposition allows us to explore the case in which newly built capacity tends to be more or less productive than mature capacity (see our Supplementary Material).

(7)
$$G_2 = \begin{cases} V_2^{nb} - I, & \text{if} \quad \theta \geq \theta_2^*, \\ E\theta^{\beta_1}, & \text{if} \quad \theta < \theta_2^*, \end{cases}$$

where E and θ_2^*, the investment-triggering output-price threshold, are parameters defined in that material. While we can interpret $V_2^{nb} - I$ as the growth option's payoff upon an exercise, $E\theta^{\beta_1}$ is the value of the real option to exercise the growth option in the future. As well-known, equation (7) suggests that the firm optimally exercises the growth option when the state variable crosses some fixed threshold from below. Importantly, the equation also implies that the growth option's elasticity is a constant $(G_2)_\theta(\theta/G_2) = \beta_1 E\theta^{\beta_1 - 1}\left(\theta/\left(E\theta^{\beta_1}\right)\right) = \beta_1$.

We can finally calculate the firm's optimal capacity, K^*, as

(8)
$$K^* = \sum_{k=1}^{2} \mathbb{I}_{\left\{\theta \geq \theta_k^*\right\}},$$

where $\mathbb{I}_{\left\{\theta \geq \theta_k^*\right\}}$ is an indicator function equal to 1 if $\theta \geq \theta_k^*$ and else 0.

D. Real Investments and the Expected Firm Return

We next study the model-implied effects of building versus buying the factory underlying the growth option on the firm's expected return. Since the only difference between buying and building is the initial uncertainty in the production costs of a newly built factory, we start off with looking into the effects of that uncertainty on the values and systematic risk of the firm's assets. Using a set of basecase parameter values, we next compute the model-implied response of the expected firm return to the firm buying or building the additional factory.

As basecase parameters, we set the annual expected return of the output-price mimicking portfolio, μ, the output-price drift rate, α, its volatility, σ, and the risk-free rate, r, to 0.08, 0.04, 0.10, and 0.01, respectively. We choose an investment cost, I, of 1.00. We set the long-run variable costs, C_1 and C_2, to 1.50 and 2.00, respectively. To isolate the effect of uncertainty, we choose $m = l$, so that the average initial log production costs of newly built capacity equal the log production costs of mature capacity.[15] We finally set the Poisson parameter, λ, to 0.20, so that, in line with Figure 2, potential reversals occur after about 5 years.[16]

1. The Effects of Learning-Induced Production Cost Uncertainty

We first examine the effects of the initial production-cost uncertainty of a newly built factory on its own value and systematic risk and those of the growth option written on it. As we said before, a newly built factory is, just like a mature factory, a call option to produce output, with the production cost the strike price. As a result, a greater (idiosyncratic) uncertainty in production costs raises the call's payoff volatility, amplifying the chance that the call ends up deeper in or out of the money. Since the call, however, benefits more from the greater upside potential than

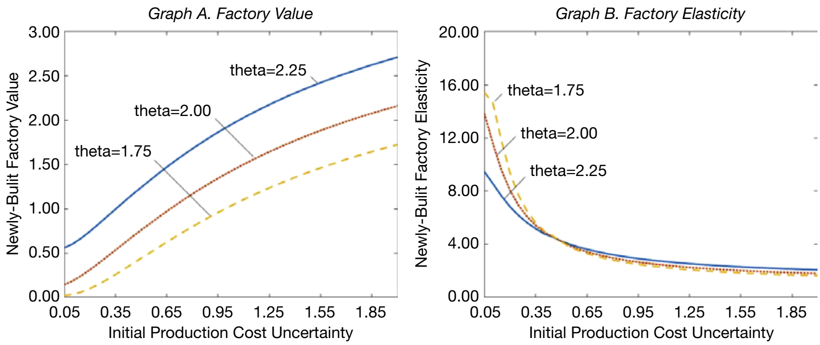
[15]Our Supplementary Material shows that setting $m \neq l$ does not materially affect our conclusions.

[16]We offer comparative statics in our Supplementary Material, showing that reasonable variations in our model input parameters yield conclusions in broad agreement with those reported in our main article.

FIGURE 3

Value and Elasticity of a Newly Built Factory

In Figure 3, we plot the value (V_2^{nb}; Graph A) and elasticity ($V_{2;\theta}^{nb}\theta / V_2^{nb}$; Graph B) of a newly built factory against the initial log production cost uncertainty, $\sigma_{c_2^t}$, for an output price θ of 1.75 (broken yellow line), 2.00 (dotted red line), or 2.25 (solid blue line) and a long-run production cost, C_2, of 2.00. We state the other parameter values in Section III.D.



it is hurt by the greater downside potential, its value rises, in agreement with the textbook argument that "options benefit from volatility." In turn, the value of the growth option also rises because it is a call option written on a call option to produce, and its value rises with uncertainty-induced increases in the value of the underlying asset.

To understand how the initial production-cost uncertainty affects the systematic risk of a newly built factory, it is easiest to i) recognize that such a factory will be deep in the money upon an investment into it, and ii) to recall that the systematic risk of an option is simply its scaled elasticity $V_\theta(\theta/V)$ (see again equation (4)). While we argue above that a greater uncertainty in production costs raises V, it also lowers V_θ, the "call delta." The reason is that the negative effect on the call's dollar sensitivity toward the underlying asset θ (which is what delta measures) induced through the greater chance that the call ends up deeper out of the money dominates the corresponding positive effect induced through the greater chance that it ends up deeper in the money. Yet, as V rises and V_θ drops, the call elasticity $V_\theta(\theta/V)$ (and thus its systematic risk) must also drop. Conversely, as shown in the penultimate paragraph of Section III.C, the systematic risk of the growth option is a constant β_1. The upshot is that the initial production-cost uncertainty does not affect the systematic risk of that option.

Figure 3 corroborates the intuition built up in this subsection. To that end, it plots the value (V; Graph A) and elasticity ($V_\theta(\theta/V)$; Graph B) of a newly built factory against the initial production-cost uncertainty, $\sigma_{c_2^t}$, for an output price, θ, of 1.75, 2.00, or 2.25 and a long-run production cost, C_2, of 2.00. While Graph A shows that a higher uncertainty raises the factory's value, Graph B reveals that it also lowers that same factory's elasticity.

2. The Response of the Expected Firm Return to Real Investments

Armed with the insights derived in Section III.D.1, we now contrast the model-implied effects of the firm buying a mature factory without initial production-cost uncertainty and building a brandnew factory with such uncertainty on its expected

TABLE 4

The Real-Options-Model Implied Relation Between Real Investments and Expected Firm Return

Table 4 presents the real-options-model implied effect of real investments on the firm's expected excess return when the firm buys a second factory with 0 (Panel A) or when it builds that same factory with a moderate (Panel B) or high (Panel C) initial production cost uncertainty. Columns 1–3 report, respectively, the firm's number of mature factories, its number of newly installed factories, and its optimal number of factories. Conversely, columns 4, 6, and 8 offer the shares of firm value attributable to the first and second installed factory and the growth option, whereas columns 5, 7, and 9 report the systematic risk of those assets, all respectively. In column 10, we state the firm's expected excess return. In each panel, we raise the output price from 0.01 below ("before investing") the second factory's optimal investment-triggering output-price threshold, θ_2^*, to 0.01 above ("directly after investing" and "long after investing") it. Also, we either assume that the newly built factory operates at its initial ("directly after investing") or its long-run ("long after investing") production costs. We describe the basecase parameter values in Section III.D. In Panels A–C, we set the initial production cost uncertainty parameter, $\sigma_{c_2^t}$, to 0, 0.50, and 1.00, respectively.

	# Factories			First Factory		Second Factory		Growth Option		
	Mature	Newly Built	Opt.	Weight	Sys. Risk	Weight	Sys. Risk	Weight	Sys. Risk	Exp. Return
	1	2	3	4	5	6	7	8	9	10
Panel A. Buying with No Cost Uncertainty ($\sigma_{c_2^t}=0.00$)										
Before investing	1	0	1	0.78	3.39			0.22	7.27	0.30
Directly after investing	2	0	2	0.72	3.35	0.28	5.34			0.28
Panel B. Building with Moderate Cost Uncertainty ($\sigma_{c_2^t}=0.50$)										
Before investing	1	0	1	0.79	4.03			0.21	7.27	0.33
Directly after investing	1	1	2	0.70	3.97	0.30	4.56			0.29
Long after investing	2	0	2	0.77	3.97	0.23	6.73			0.32
Panel C. Building with Moderate Cost Uncertainty ($\sigma_{c_2^t}=1.00$)										
Before investing	1	0	1	0.77	5.62			0.23	7.27	0.42
Directly after investing	1	1	2	0.60	5.50	0.40	3.27			0.32
Long after investing	2	0	2	0.84	5.50	0.16	7.28			0.40

return. To do so, Table 4 reports the expected excess firm return, $E[R]-r$, under an initial uncertainty, $\sigma_{c_2^t}$, of 0 (Panel A; buying without uncertainty), 0.50 (Panel B; building with moderate uncertainty), and 1.00 (Panel C; building with high uncertainty) before the investment, directly after, and once the newly built factory has matured (if applicable). To prompt the firm to invest into the second factory without meaningfully altering the moneyness of its assets (and thus keeping other mechanisms, as, e.g., operating leverage, constant), we simply raise the output price θ from slightly (i.e., 0.01) below the investment-triggering threshold θ_2^* to slightly (i.e., 0.01) above that threshold. In addition to $E[R]-r$, the table further reports the number of mature and newly built assets-in-place, the optimal number of those assets, the shares of firm value attributable to mature and newly built assets-in-place and growth options, as well as the elasticities of those assets.

Panel A of Table 4 shows that the firm's expected excess return changes only marginally in response to the firm buying a mature factory without initial production cost uncertainty, from about 30% before the acquisition to about 28% after. The only marginal change occurs since i) the investment alters the firm's asset mix from one asset-in-place plus one growth option to two assets-in-place; ii) the new asset-in-place's value exceeds the growth option's value by I at the investment threshold θ_2^* (see equation (7)); and iii) the systematic risk of assets-in-place is bounded from above by that of growth options in the standard model without the above uncertainty (see Aretz and Pope (2018) for the formal proof). The upshot is that the investment replaces a higher-risk (elasticity: 7.27) with a lower-risk (5.34) option, reducing the expected excess return (see columns 7 and 9). Yet, in addition, it also skews firm value toward the higher-risk second asset (initial vs. later weight: 22% vs. 28%), raising that same return (see columns 6 and 8). Given those opposing forces, the overall response of the firm's expected excess return is only mildly negative. Even more problematically, the negative response does not revert over time, deviating from our empirical evidence.

In Panels B and C of Table 4, we next investigate how the firm's expected excess return responds to it building a modern factory with initial production-cost uncertainty. The panels suggest that the expected excess return drops more significantly due to the firm building (rather than buying) a modern factory with $\sigma_{c_2^t} = 0.50$ or 1.00, with the drop, however, almost completely reversing after the newly built factory has matured. Looking, e.g., into the high-uncertainty case with $\sigma_{c_2^t} = 1.00$, Panel C reports that the expected excess return initially drops from about 42% to about 32% but later reverses to about 40%. To better grasp these results, we notice that, in the high-uncertainty building case, the investment replaces a growth option with the same risk as in the buying case (elasticity: 7.27) with a much-lower-risk asset-in-place (3.27), amplifying the corresponding drop in the expected excess return (see columns 7 and 9). In addition, the uncertainty, however, also lowers the risk of the second asset-in-place (3.27) relative to the first (5.50), dampening (or in the high uncertainty case even reversing) the increase in that same return due to the firm's value being skewed toward the second asset (see columns 6 and 8). The overall response of the firm's expected excess return is thus far more negative in the building relative to the buying case, with the negative response however almost fully reversing as the initial cost uncertainty resolves.

Overall, this section suggests that a real options model in which the initial production costs of newly built capacity are uncertain due to firms learning how to optimally operate that capacity can reproduce our empirical evidence that the subsample of firms physically building additional productive capacity drives the investment anomaly.

IV. Empirical Tests of Our Uncertainty Explanation

In this section, we empirically assess the new testable implications of our uncertainty explanation for why constructing firms drive the investment anomaly. We start off with the implication that the profits of firms with newly built capacity should be less sensitive to aggregate conditions than those of other firms. We subsequently turn to the implication that the higher uncertainty characterizing firms with newly built capacity should be detectable in analyst earnings forecast data. We finally test the implication that the uncertainty characterizing newly built capacity should be higher in industries exposed to more technological innovation.

A. The Profit Sensitivity of Firms with Newly Built Capacity

In contrast to theoretical studies analyzing the effects of financial uncertainty (as, e.g., Johnson (2004)), we conjecture that firms with newly built capacity are exposed to high *real* uncertainty stemming from idiosyncratic shocks to their

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profits. In turn, these shocks lower the sensitivity of firms with newly built capacity to aggregate conditions, as captured by the output price θ in our model. In the spirit of Fama and French (1995), we should thus be able to detect the lower sensitives in firms' financial data. To test that conjecture, we rely on a panel regression of a firm's profit growth on the change in its industry's mean-output-price interacted with a dummy variable indicating whether the firm will soon obtain, has recently obtained, or has some time ago obtained newly built capacity, the main effects, control variables, and fixed effects. To be more specific, we estimate the following panel regression model:

$$\begin{aligned}(9)\qquad \Delta\text{PROFIT}_{i,k,t} = {} & \beta(\Delta\text{OUTPUT\_PRICE}_{k,t} \times \text{NEWLY\_BUILT}_{i,k,t}) \\ & + \gamma\Delta\text{OUTPUT\_PRICE}_{k,t} + \delta\text{NEWLY\_BUILT}_{i,k,t} \\ & + \eta'\text{CONTROLS}_{i,k,t} + \alpha_i + \alpha_t + \varepsilon_{i,k,t},\end{aligned}$$

where ΔPROFIT is the change in firm i's quarterly operating profits (Compustat items: saleq-cogsq) over calendar quarter t scaled by assets (atq) at the quarter's start, ΔOUTPUT_PRICE is the change in industry k's mean output price over that quarter, NEWLY_BUILT $\in$ {PRE_CONSTRUCTION, POST_CONSTRUCTION, LONG_POST_CONSTRUCTION}, and CONTROLS is a vector of control variables. In turn, PRE_CONSTRUCTION (POST_CONSTRUCTION) [LONG_POST_CONSTRUCTION] is a dummy variable equal to 1 if firm i reports positive PPE-CIP expenses over the next 3 years (the past 3 years) [the 3 years before the prior three] and else 0.[17] Finally, α_i is a firm and α_t a time fixed effect, β, γ, and δ are scalar parameters, and η is a parameter vector.

We calculate ΔOUTPUT_PRICE by first aggregating firm sales (saleq) at the Chang and Hwang (2015) industry level and then computing industry sales growth over quarter t.[18] Using quarterly total output growth for each industry from the Federal Reserve's industrial production database, we next back out ΔOUTPUT_PRICE from the accounting identity that industry sales growth is industry mean output price growth times industry quantity growth.[19] Our controls are lagged PROFIT_GROWTH, QUARTERLY_RETURN, MOMENTUM,

[17]In the Supplementary Material, we confirm that our main conclusions in Section IV are robust to the choice of windows used to define the pre-construction, post-construction, and long-post-construction periods.

[18]See Table A3 in Appendix A in this article for industry definitions. Notice that we only use industries with consistently more than ten firms and that, to avoid spurious results, we compute industry sales growth separately by firm, with the growth value for firm i excluding the sales of that firm.

[19]The sales of firm i over quarter t, SALES, are its output quantity, QUANTITY, multiplied by its (average) output price, PRICE, over that quarter. Summing that identity over all N firms in industry k, we obtain $\sum_{i=1}^{N}\text{SALES}_{i,k,t} = \sum_{i=1}^{N}\left(\text{QUANTITY}_{i,k,t} \times \text{PRICE}_{i,k,t}\right)$. Multiplying and dividing the right-hand side by the total output of the N firms in industry k in that quarter, we obtain the accounting identity:

$$(10)\qquad \sum_{i=1}^{N}\text{SALES}_{i,k,t} = \sum_{i=1}^{N}\text{QUANTITY}_{i,k,t} \times \left(\sum_{i=1}^{N}\frac{\text{QUANTITY}_{i,k,t}}{\sum_{i=1}^{N}\text{QUANTITY}_{i,k,t}} \times \text{PRICE}_{i,k,t}\right).$$

Dividing the identity for quarter t by the identity for quarter $t-1$, we derive the desired result.

MARKET_SIZE, and BOOK_TO_MARKET. See Table A1 in Appendix A in this article for more details about the controls. We winsorize each continuous variable at the first and last percentile per quarter. For the sake of comparability, we only use a firm-quarter observation in the panel regressions if the corresponding firm is included in our asset pricing tests conducted in Section II over the prior three calendar years.

Table 5 reports the panel regression results obtained from the full sample (columns 1 and 2) and from subsamples with an average past 3 years ΔOUTPUT_PRICE above (columns 3 and 5) and below (columns 4 and 6) the median. While plain numbers are parameter estimates, the numbers in square brackets are White (1980) t-statistics. The table vividly supports our first new testable implication, showing that firms with newly built capacity have a temporarily lower profit sensitivity than others. Specifically, column 1 reveals that firms with newly built capacity have a similar sensitivity (of around 0.40) as others over the 3 years before the capacity is constructed. Strikingly, however, column 2 demonstrates that their sensitivity becomes 0.23 (t-stat: −3.62) lower relative to the others over the 3 years after the capacity has been constructed. Separately contrasting that difference across good (mean ΔOUTPUT_PRICE ≥ median) and bad (< median) industry states, columns 3 and 4 indicate that the difference is much starker in bad states, in line with Figure 3 showing that the effect of uncertainty is stronger when the firm is less profitable. Finally, columns 5 and 6 suggest that the sensitivity of firms with newly built capacity eventually becomes similar to that of the others again.

B. The Analyst Forecasts of Firms with Newly Built Capacity

We next test the implication that the higher uncertainty characterizing firms with newly built capacity should also be detectable in non-stock-and-accounting data. To do so, we look into analyst earnings forecast data, arguing that analysts should be less able to accurately predict the earnings of firms with newly built capacity due to their more uncertain profits.[20] To assess that conjecture, we estimate the following panel regression model:

$$(11) \qquad \text{ABS\_FORECAST\_ERROR}_{i,t} = \beta\text{NEWLY\_BUILT}_{i,t} + \gamma'\text{CONTROLS}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t},$$

where ABS_FORECAST_ERROR is the absolute value of the actual earnings-per-share (EPS) minus their consensus (median) forecast scaled by the actual EPS (see, e.g., Loh and Mian (2006) and Bebchuk, Cohen, and Charles (2013)), NEWLY_BUILT ∈ {PRE_CONSTRUCTION, POST_CONSTRUCTION, LONG_POST_CONSTRUCTION}, and CONTROLS is a vector of control variables. We define the variables included in NEWLY_BUILT as in Section IV.A. In line with the literature, the control variables are MARKET_SIZE, BOOK_TO_MARKET, MOMENTUM, VOLATILITY, TURNOVER, FORECAST_AGE, and ANALYST_COVERAGE. Again, see Table A1 in Appendix A in this article for more

[20]We acknowledge that, in practice, a greater profit uncertainty may not necessarily come from a greater cost uncertainty but could equally well come from a greater output price uncertainty.

TABLE 5

Profit Regressions on Industry Conditions Interacted with Construction

Table 5 presents the results from panel regressions of a firm's profit growth over calendar quarter t on its industry's contemporaneous output price growth, output price growth interacted with a dummy variable equal to 1 if the firm engages in construction work over the following 3 years (PRE_CONSTRUCTION), the prior three (POST_CONSTRUCTION), or the 3-year period before the prior 3 years (LONG_POST_CONSTRUCTION) and else 0, controls, and firm and time fixed effects. While columns 1 and 2 show the results from full-sample regressions, columns 3–6 show those from subsample regressions on observations with a past 3-year industry output price growth above (columns 3 and 5) and below (columns 4 and 6) the median. Plain numbers are estimates, while the numbers in square brackets are White (1980) t-statistics. See Tables A1 and A3 in Appendix A for variable as well as industry definitions, respectively.

			Subsamples			
			Price Growth		Price Growth	
	Full Sample	Full Sample	High	Low	High	Low
	1	2	3	4	5	6
ΔOUTPUT_PRICE (ΔOP)	0.39 [7.47]	0.40 [8.33]	0.38 [4.91]	0.46 [6.80]	0.31 [3.80]	0.18 [2.37]
ΔOP × PRE_CONSTRUCTION	0.02 [0.09]					
ΔOP × POST__CONSTRUCTION		−0.23 [−3.62]	−0.15 [−1.48]	−0.34 [−3.76]		
ΔOP × LONG_POST_CONSTRUCTION					−0.09 [−0.83]	−0.25 [−1.96]
LAG_PROFIT_GROWTH	−20.06 [−23.39]	−19.58 [−32.14]	−19.41 [−21.62]	−21.19 [−23.72]	−17.83 [−17.59]	−20.50 [−19.85]
QUARTERLY_RETURN	1.10 [15.67]	0.95 [20.66]	1.05 [15.83]	0.84 [12.35]	0.89 [12.39]	0.82 [10.85]
MOMENTUM	0.25 [8.27]	0.21 [9.60]	0.20 [6.24]	0.23 [6.99]	0.20 [5.76]	0.22 [5.95]
MARKET_SIZE	−0.22 [−7.30]	−0.17 [−9.10]	−0.22 [−7.34]	−0.16 [−5.63]	−0.20 [−6.49]	−0.11 [−3.47]
BOOK_TO_MARKET	−0.39 [−10.05]	−0.32 [−13.54]	−0.36 [−9.32]	−0.29 [−8.75]	−0.31 [−7.93]	−0.24 [−6.52]
PRE_CONSTRUCTION	0.03 [0.37]					
POST_CONSTRUCTION		−0.01 [−0.24]	−0.02 [−0.27]	−0.02 [−0.34]		
LONG_POST_CONSTRUCTION					−0.01 [−0.23]	0.03 [0.37]
Firm/time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.06	0.05	0.05	0.06	0.04	0.05

details about the controls. While α_i is a firm and α_t a time fixed effect, β is a scalar parameter and γ a parameter vector. Finally, we use the same winsorization rules and include the same observations as in Section IV.A.

Using the same conventions as Table 5, Table 6 presents the panel regression results. The table validates our second new testable implication, showing that analysts find it temporarily more difficult to accurately predict the earnings of firms with newly built capacity. To be more specific, column 1 demonstrates that analysts predict the earnings of firms with newly built capacity with a similar accuracy as those of others over the 3 years before the capacity is constructed. Importantly, however, column 2 suggests that they make about 4-percent-point larger forecast errors (t-stat: 4.07) in case of firms with newly built capacity relative to others over the 3 years after the capacity has been constructed. Finally, column 3 reveals that the

TABLE 6

Absolute Forecast Error Regressions on Construction

Table 6 presents the results from panel regressions of a firm's absolute analyst earnings-forecast error scaled by realized earnings on a dummy variable equal to 1 if the firm engages in construction work over the following 3 years (PRE_CONSTRUCTION), the prior three (POST_CONSTRUCTION), or the 3-year period before the prior 3 years (LONG_POST_CONSTRUCTION) and else 0, controls, and firm and time fixed effects. Plain numbers are coefficient estimates, while the numbers in square brackets are White (1980) *t*-statistics. See Table A1 in Appendix A for the variable definitions.

	1	2	3
PRE_CONSTRUCTION	0.02 [1.42]		
POST_CONSTRUCTION		0.04 [4.07]	
LONG_POST_CONSTRUCTION			0.03 [3.18]
MARKET_SIZE	−0.12 [−17.81]	−0.12 [−25.18]	−0.11 [−22.36]
BOOK_TO_MARKET	0.04 [4.49]	0.04 [6.69]	0.04 [7.37]
MOMENTUM	−0.05 [−8.06]	−0.04 [−9.85]	−0.03 [−6.96]
VOLATILITY	0.21 [7.09]	0.18 [8.78]	0.21 [8.88]
TURNOVER	−0.03 [−0.82]	−0.02 [−1.03]	−0.06 [−2.51]
FORECAST_AGE	0.08 [5.62]	0.07 [6.49]	0.07 [6.23]
ANALYST_COVERAGE	−0.38 [−4.35]	−0.35 [−5.97]	−0.35 [−5.75]
Firm/time FEs	Yes	Yes	Yes
Adj. R^2	0.18	0.16	0.17

difference in analysts' predictive ability across firms with newly built capacity and others shrinks again as we move away from the capacity installation date.

C. The Effect of Construction in High- Versus Low-Tech Industries

We finally study the implication that the conditional effect of construction on the investment anomaly is stronger in industries more exposed to technological progress. The reason is that, in such industries, newly built capacity plausibly differs more significantly from existing capacity, forcing the firm to engage in more trial-and-error to find the optimal input combination and, in turn, boosting the uncertainty characterizing newly built capacity. To test that conjecture, we simply repeat the FM regression of stock returns on INVESTMENT, an interaction between INVESTMENT and CONSTRUCTION, CONSTRUCTION, and controls in column 2 of Table 3 separately on subsamples formed according to industry-specific measures of technological progress.

We rely on three well-established approaches to measure the amount of innovation within an industry. First, in line with Kogan, Papanikolaou, Seru, and Stoffman (2017), we compute the total number of citations of all patents held by firms in a 2-digit SIC industry over the past 3 years at the end of June of each year *t*, classifying industries with a value above the median as high-tech and others as

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TABLE 7

Regressions of Stock Returns on Investment Interacted with Construction Separately Run on High- Versus Low-Tech Industry Subsamples

Table 7 presents the results from Fama and MacBeth (1973) regressions of stock returns over month *t* on combinations of investment, construction, and control variables measured until the end of month *t* − 1. In column 1, we report the results from a full-sample regression on INVESTMENT, an interaction between INVESTMENT and CONSTRUCTION, CONSTRUCTION, and the controls. In the remaining columns, we repeat that regression on industry subsamples formed according to whether the citation count of all patents issued to firms in a 2-digit SIC industry over the last 3 years is above (column 2) or below (column 3) the median; the average exogenous R&D to which the firms in a 2-digit SIC industry are exposed over the last 3 years is above (column 4) or below (column 5) the median; or the existing literature classifies the industry as a high (column 6) or low (column 7) tech industry. The plain numbers are monthly premium estimates, in percentage. The numbers in square brackets are Newey and West (1987) *t*-statistics with a 6-month lag length. See Table A1 in Appendix A for more details about variable definitions.

		High- Versus Low-Tech Subsamples					
		# Industry Patents		R&D Exposure		High-Tech Industry	
	Full Sample	High	Low	High	Low	Yes	No
	1	2	3	4	5	6	7
INVESTMENT	−0.85	−0.94	−0.75	−1.32	−0.08	0.06	−0.61
	[−2.06]	[−1.89]	[−1.78]	[−2.62]	[−0.19]	[0.08]	[−1.53]
INVESTMENT × CONSTRUCTION	−20.97	−32.46	−0.49	−24.95	−17.51	−48.35	−4.14
	[−2.50]	[−2.71]	[−0.04]	[−2.43]	[−1.03]	[−2.56]	[−0.42]
CONSTRUCTION	0.47	2.14	−2.28	1.05	−0.46	4.79	−1.15
	[0.33]	[1.40]	[−1.15]	[0.69]	[−0.20]	[2.02]	[−0.69]
MARKET_BETA	0.00	−0.03	0.04	−0.02	−0.05	−0.20	0.02
	[0.00]	[−0.12]	[0.22]	[−0.11]	[−0.23]	[−0.91]	[0.08]
MARKET_SIZE	−0.03	−0.05	−0.01	−0.05	−0.00	−0.05	−0.00
	[−0.75]	[−0.96]	[−0.16]	[−1.01]	[−0.04]	[−0.86]	[−0.11]
BOOK_TO_MARKET	0.22	0.22	0.36	0.23	0.32	0.26	0.33
	[2.57]	[2.41]	[3.79]	[2.62]	[2.80]	[2.66]	[3.84]
MOMENTUM	0.91	0.61	1.20	0.77	0.87	0.52	1.09
	[4.16]	[2.91]	[4.92]	[3.62]	[3.41]	[2.53]	[4.59]
PROFITABILITY	0.66	0.51	1.21	0.58	0.86	0.66	0.90
	[2.88]	[1.97]	[6.08]	[2.24]	[3.14]	[2.08]	[5.16]
Constant	0.90	1.21	0.43	1.23	0.59	1.49	0.52
	[2.05]	[2.48]	[1.02]	[2.58]	[1.31]	[2.73]	[1.26]

low-tech. Consistent with Bloom, Schankerman, and Van Reenen (2013), we also compute the average amount of exogenous R&D in a firm's technology space over all firms in a 2-digit SIC industry over the last 3 years at the end of June of each year *t*, again classifying industries with a value above the median as high-tech and the others as low-tech. In each case, we use the thus derived classification from July of year *t* to June of year $t+1$. We finally follow Grullon, Lyandres, and Zhdanov (2012) and classify the medical equipment (12); pharmaceutical products (13); electrical equipment (22); communications (32); computers (35); electronic equipment (37); and measuring and control equipment (38) Fama–French 49 industries as high-tech and others as low-tech.[21]

Using conventions identical to Table 3, Table 7 reports the results from the FM regressions run on the high- versus low-tech industry subsamples. While column 1 repeats the full-sample regression results for convenience, columns 2, 4, and 6 (columns 3, 5, and 7) present those obtained from the high (low) tech subsamples

[21]See Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/), for more details about the definition and construction of the Fama–French 49 industry classification.

defined according to patent citations, exogenous R&D exposure, and industry definitions, respectively. The table corroborates our final new testable implication, showing that the effect of CONSTRUCTION on the pricing of INVESTMENT is far more pronounced in high-tech industries. Using patent citations to measure the technological progress in an industry, columns 2 and 3, e.g., demonstrate that while the slope coefficient of the INVESTMENT–CONSTRUCTION interaction term is highly significantly negative in industries with many citations (t-stat: −2.71), that same slope coefficient does not attract significance at conventional levels in industries with few citations (t-stat: −0.04).

D. Alternative Explanations

While the prior subsections give evidence corroborating our uncertainty explanation for why constructing firms drive the investment anomaly, our Supplementary Material offers further evidence refuting several plausible alternative explanations. To be more specific, that material shows that our main empirical evidence is unlikely to be caused by i) variations in investment intensity, market size, and growth option availability across constructing and non-constructing firms; ii) the financing of construction projects through overvalued equity; and iii) anecdotal evidence that construction projects often go significantly overbudget.

V. Concluding Remarks

We offer evidence that the subsample of firms physically building additional production capacity almost entirely drives the negative but non-persistent relation between real investments and future stock returns. We develop a real options model to rationalize that evidence based on the idea that firms have to experiment with newly built capacity to learn how to operate it at its lowest feasible cost, inducing idiosyncratic uncertainty in that capacity's production cost over some initial period. In turn, this uncertainty drags down the firm's expected return until it eventually disappears. We finally conduct additional tests supporting the new testable implications of our uncertainty explanation for our main evidence.

Appendix A. Definitions and Data Sources

In this appendix, we offer variable and industry definitions, outline our data sources, and present descriptive statistics. We first introduce our control variables as well as concisely summarize how we calculate the analysis variables used in all our empirical tests (see Table A1). We next outline our data sources. We then discuss the descriptive statistics for the main analysis and control variables used in our asset pricing tests, reporting those statistics in Table A2. Finally, Table A3 offers more details about the definitions of the industries used in our profit growth panel regressions.

A.1 Control Variables

We use a standard set of controls in our asset pricing tests. Our portfolio sorts control for the Fama and French (2015) 5-factor-model or Hou et al. (2015) q-theory

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TABLE A1

Variable Definitions

Table A1 gives the definitions of the variables used in our asset pricing and supplementary panel regression tests. The mnemonics of the data providers are in parentheses. We notice that, in contrast to the asset pricing controls, the analyst forecast error controls are measured at the end (or closest to the end) of the fiscal quarter during which an analyst made the corresponding earnings forecast.

Variable Name	Variable Definition
Panel A. Investment and Construction Proxies	
INVESTMENT	The change in gross property, plant, and equipment (ppegt) over the fiscal year ending in calendar year $t-1$ scaled by total assets (at) at the start of that fiscal year.
CONSTRUCTION	The ratio of gross property, plant, and equipment under construction (fatc) from the fiscal year ending in calendar year $t-1$ to total assets (at) at the start of that fiscal year.
DUMMY_CONSTRUCTION	A binary variable equal to 1 if CONSTRUCTION is positive and else 0.
RANK_CONSTRUCTION	A variable taking the value of 0 if CONSTRUCTION is 0 and else the rank of the remaining CONSTRUCTION values.
Panel B. Control Variables	
MARKET_BETA	The slope coefficient from a stock-level regression of excess return (ret) on excess market return, where the regression is run using daily data over the prior 12 months. We require a sample size of at least 200 non-missing observations for us to run the regression.
MARKET_SIZE	Log of the product of the stock price (abs(prc)) times common shares outstanding divided by 1,000 (shrout).
BOOK_TO_MARKET	Log of the ratio of book value-to-market value of equity (abs(prc) × shrout), where the book value of equity is equal to total assets (at) minus total liabilities (lt) plus deferred taxes (txditc, 0 if missing) minus preferred stock (pstkrv, pstkl, pstk, or 0, in that order of availability). While the market value of equity is from the end of December of calendar year $t-1$, the variables underlying the book value of equity are from the fiscal year end in calendar year $t-1$.
MOMENTUM	Log of the compounded stock return (ret) over the period from month $t-12$ to month $t-2$. We require the stock return to be non-missing for at least 9 months over that period.
PROFITABILITY	Ratio of sales (sale) net of costs of goods sold (cogs), selling, general, and administrative expenses (xsga), and interest expenses (xint) to the book value of equity, where the book value of equity is total assets (at) minus total liabilities (lt) plus deferred taxes (txditc, 0 if missing) minus preferred stock (pstkrv, pstkl, pstk, or 0, in that order of availability). All variables are from the fiscal year end in calendar year $t-1$.
Panel C. Additional Variables	
ΔPROFIT	The change in gross profits (saleq minus cogsq) over calendar quarter t scaled by total assets (atq) at the start of that quarter.
ΔOUTPUT_PRICE	The ratio of the gross-sales growth of an industry over calendar quarter t to the gross production growth of that industry over the same quarter minus one. In case of firm i belonging to industry k, we estimate industry k's total sales by aggregating the sales (saleq) of all firms belonging to that industry except for firm i. We estimate an industry's production growth using its industrial production index obtained from the Federal Reserve's G.17 database.
CONSTRUCTION	A binary variable equal to 1 if a firm has a positive CONSTRUCTION value in at least 1 year over the 3-year period after (PRE_CONSTRUCTION), before (POST_CONSTRUCTION), or 3-years before (LONG_POST_CONSTRUCTION) the current year and else 0.
LAG_PROFIT_GROWTH	The one-quarter lagged value of ΔPROFIT.
QUARTERLY_RETURN	The compounded stock return (ret) over calendar quarter t.
VOLATILITY	The standard deviation of daily stock returns estimated over the prior 12 months times the square root of 252. We require stock returns to be non-missing for at least 9 months over that period.
TURNOVER	The average ratio of monthly trading volume to shares outstanding estimated over the prior 3 months.
FORECAST_AGE	The gap between earnings announcement date and earnings forecast date averaged over all outstanding forecasts.
ANALYST_COVERAGE	The number of analysts issuing an earnings forecast.

benchmark factors excluding their investment factors.[22] Our FM regressions control for MARKET_BETA, MARKET_SIZE, BOOK_TO_MARKET, MOMENTUM, and PROFITABILITY. We calculate MARKET_BETA as the slope coefficient from a time-

[22]The 5-factor-model factors consist of MKT, SMB, HML, CMA, and RMW, while the q-theory factors consist of MKT, ME, IA, and ROE. See Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/), for more details about the 5-factor-model factors. Conversely, see Lu Zhang's website (https://global-q.org/factors.html/), for more details about the q-theory factors.

TABLE A2

Descriptive Statistics

Table A2 presents descriptive statistics for INVESTMENT, CONSTRUCTION, and DUMMY_CONSTRUCTION (Panel A) and the Pearson cross-correlations between the joint set of the investment and construction variables and our controls (Panel B). The descriptive statistics include the mean, the standard deviation, skewness, kurtosis, and several percentiles. We calculate the table entries first by sample month and then average over our sample period. Except for skewness and kurtosis, the statistics in columns 1 and 2 in Panel A are in percentage. See Table A1 in Appendix A for more details about variable definitions.

	INVESTMENT	CONSTRUCTION	DUMMY_CONSTRUCTION
	1	2	3
Panel A. Descriptive Statistics			
Mean	9.10	1.09	0.37
Std. dev.	12.50	2.43	0.48
Skewness	3.26	3.34	0.54
Kurtosis	15.81	15.66	1.41
Percentile 1	0.14	0.00	0.00
Percentile 5	0.57	0.00	0.00
First quartile	2.38	0.00	0.00
Median	5.07	0.00	0.01
Third quartile	10.32	0.96	1.00
Percentile 95	32.25	5.78	1.00
Percentile 99	78.23	14.38	1.00
Panel B. Pearson Correlations			
CONSTRUCTION	0.20		
DUMMY_CONSTRUCTION	0.00	0.59	
MARKET_BETA	0.09	0.04	−0.01
MARKET_SIZE	0.01	0.12	0.11
BOOK_TO_MARKET	−0.06	−0.06	−0.02
MOMENTUM	−0.07	−0.02	0.01
PROFITABILITY	0.04	0.05	0.06

series regression of a stock's daily return on the daily market return over the prior 12 months, imposing a minimum sample size of 200 observations.[23] MARKET_SIZE is the log of the product of common shares outstanding and share price at the end of calendar month $t-1$. We calculate BOOK_TO_MARKET as the log ratio of the book value of equity from the fiscal year ending in calendar year $t-1$ to the market value of equity from the end of calendar year $t-1$ and use the thus calculated value from June of calendar year t to May of calendar year $t+1$. MOMENTUM is the compounded stock return over calendar months $t-12$ to $t-2$. We calculate PROFITABILITY as sales minus costs of goods sold (COGS), selling, general, and administrative (SG&A) expenses, and interest expenses scaled by book equity for the fiscal year ending in calendar year $t-1$ and use the thus calculated value from June of calendar year t to May of calendar year $t+1$.

A.2 Data Sources

Our market data come from CRSP, the accounting data from Compustat, the analyst data from IBES, and the benchmark factor as well as the risk-free rate of return data from Kenneth French's and Lu Zhang's websites. We study the common stocks

[23]We also ran Lewellen and Nagel (2006) time-series regressions of a stock's daily return on the contemporaneous, 1-day-lagged, and the sum of the 2-, 3-, and 4-day-lagged daily market returns. Using the sum of the slope coefficients as alternative market beta estimate, we obtain identical conclusions as in our main tests.

TABLE A3

Industry Classifications

Table A3 presents the 32 NAICS industries used to construct ΔOUTPUT_PRICE.

NAICS	Industry Name
315	Apparel
316	Leather and allied products
323	Printing and related support activities
324	Petroleum and coal products
3114	Fruit and vegetable preserving and specialty food
3116	Animal slaughtering and processing
3119	Other food
3121	Beverage
3221	Pulp, paper, and paperboard mills
3222	Converted paper products
3251	Basic chemicals
3252	Resin, synthetic rubber, and artificial and synthetic fibers and filaments
3253	Pesticide, fertilizer, and other agricultural chemicals
3254	Pharmaceuticals and medicine
3256	Soap, cleaning compounds, and toilet preparation
3261	Plastic products
3311,2	Iron and steel products
3314	Nonferrous metal (except aluminum) production and processing
3329	Other fabricated metal products
3331	Agriculture, construction, and mining machinery
3332	Industrial machinery
3333,9	Commercial and service industry machinery and other general purpose machinery
3334	Ventilation, heating, air-conditioning, and commercial refrigeration equipment
3343	Audio and video equipment
3345	Navigational, measuring, electromedical, and control instruments
3353	Electrical equipment
3359	Other electrical equipment and components
3361	Motor vehicles
3363	Motor vehicle parts
3364	Aerospace products and parts
3371	Household and institutional furniture and kitchen cabinets
3391	Medical equipment and supplies

(share codes: 10 and 11) of firms traded on the NYSE, AMEX, and Nasdaq. To ensure our sample firms use at least some physical assets in their operations, we exclude financial (SIC codes: 6000 to 6999), utility (4900 to 4949), and service (7000 to 8999) firms.[24] To benchmark our investing firms against non-investing (and not also disinvesting) firms, we further drop firms with negative INVESTMENT values. To mitigate microstructure biases, we eliminate firms with a market size below the first quartile at the end of June of calendar year t and/or sales below \$25 million over the fiscal year ending in calendar year $t-1$, from the July of year t to June of year $t+1$ sample period. In line with Shumway (1997) and Bali, Brown, and Tang (2017), we set a stock's return to its CRSP delisting return whenever the delisting return is non-missing.[25] We winsorize all analysis variables except the stock return at the first and 99th percentiles per month. We set missing PPE-CIP values to 0 in our main tests, but in our Supplementary Material conduct a robustness test in which we exclude firms with

[24]While it is common to exclude financial and utility firms, we acknowledge that it is less common to also exclude service firms. We do so since investments into physical capacity (as captured by INVESTMENT) play a less important role for them than for others. Despite that, our Supplementary Material shows that keeping service firms in our sample does not greatly alter the conclusions extracted from our empirical work.

[25]Whenever the delisting return is missing but the delisting code is not, we set the stock return to −30% for delisting codes 500, 520, 551 to 573, 574, 580, and 584 and −100% for others.

missing PPE-CIP values. Due to the availability of the PPE-CIP data, our sample period is July 1986 to Dec. 2016.

A.3 Descriptive Statistics

In Table A2, we offer descriptive statistics for INVESTMENT, CONSTRUCTION, and DUMMY_CONSTRUCTION and the Pearson correlations for the joint set of those variables and our controls in Panels A and B, respectively. We compute both the descriptive statistics and correlations first by sample month and then average over our sample period. Panel A suggests that the mean (median) firm in our sample data raises its PPE by 9.10% (5.07%) of its assets in the average year (see column 1). Column 2 reveals that about 12% (0%) of that change is attributable to firms building additional capacity. Although that fraction may seem small, we stress that it should be treated as a lower bound since we do not observe all construction expenses (recall Section II.A), and the change in PPE includes maintenance and upgrading expenses. Looking into their first three higher moments, INVESTMENT and CONSTRUCTION are both highly volatile and right-skewed. While about three quarters of our sample firms raise their PPE by less than 10% in the average year, the remainder raises it by close to 25%, consistent with Doms and Dunne's (1998) and Cooper and Haltiwanger's (2006) evidence that corporate investment is spikey. Focusing on sample firms with a positive PPE-CIP balance, while about 60% of them have a negligible fraction of assets-under-construction, the remainder has a far more significant fraction of such assets (average: about 5%). Finally, column 3 suggests that about 37% of our sample firms are engaged in construction work in the average year.

Panel B demonstrates that INVESTMENT and CONSTRUCTION share a significantly positive average cross-sectional correlation of 0.20, indicating that the PPE-CIP balance at the end of a fiscal year explains a meaningful fraction of the change in PPE over that year. In contrast, the two variables do not share high average correlations with the controls. The exceptions are the moderately positive average correlations of CONSTRUCTION or DUMMY_CONSTRUCTION with MARKET_SIZE of 0.12 and 0.10, respectively. The moderately positive correlations with MARKET_SIZE suggest that larger firms are more prone to have assets-under-construction.

Supplementary material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109024000024.

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