What Makes a Firm Complex?

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Abstract

We develop a revealed measure of firm complexity based on the predictable errors professional analysts make when updating earnings forecasts. By separating firm-specific errors from analyst-specific biases and updating tendencies, our measure captures how difficult firms are to understand, rather than relying on researcher-defined characteristics. We show that revealed complexity systematically amplifies stock return anomalies, particularly those related to profitability and quality. These anomalies are concentrated among the most complex firms and are not statistically distinguishable from zero among the least complex firms. Our findings suggest that difficulties in interpreting firm fundamentals contribute to return predictability and provide a new approach to measuring complexity in financial markets.

1 Introduction

Information about firms plays a central role across economics. In financial markets, whether and how investors incorporate information about firms into prices is fundamental to market efficiency. In macroeconomics, frictions in information processing and belief formation shape expectations, price adjustment, and the transmission of aggregate shocks. In corporate finance, informational differences between agents shape incentives and financial contracting. In household finance, limited financial knowledge and sophistication influence stock market participation, portfolio choice, and investment performance.

Underlying these questions is a more basic distinction: having information about a firm is not the same as understanding it. Even when information is publicly available, interpreting its implications for a firm's future performance may be straightforward for some firms and difficult for others. A firm's complexity may therefore matter independently of the amount of information disclosed or the sophistication of the agent processing it. Yet measuring this complexity is challenging. Observable firm characteristics, such as size, age, industry, or the structure of its operations, may proxy for complexity, but need not capture how difficult the firm actually is to understand.

In this paper, we propose a revealed measure of firm complexity based on the predictable mistakes professional financial analysts make when updating their beliefs about firms. Our starting point is a simple thought experiment: consider the same analyst forecasting the earnings of two different firms. If the analyst makes larger predictable updating errors for one firm than the other, we consider that firm more complex. This approach defines complexity through the difficulty agents reveal in processing information, rather than through characteristics researchers specify and impose.

We implement this idea using individual analysts' earnings forecast revisions. By separating systematic updating errors attributable to analysts from those attributable to firms, we construct a firm-level measure of revealed complexity. We then examine whether this measure helps explain where return predictability arises in financial markets.

We find that revealed complexity systematically amplifies stock return anomalies associated with profitability and quality. Across 153 documented anomaly characteristics, profitability and quality are the only factor themes that exhibit statistically significant amplification in all three of our main specifications, including those controlling for firm size and idiosyncratic volatility. Moreover, profitability and quality anomalies are not statistically distinguishable from zero among the least complex firms and are concentrated among the most complex firms. These findings are consistent with the interpretation that difficulty in processing information about firm fundamentals contributes to return predictability, particularly for classes of factors that are fundamentals-related.

More broadly, our approach provides a way to measure an economically important but difficult-to-observe feature of firms. Rather than inferring complexity from what firms look like, we infer it from the systematic difficulty that informed agents experience in understanding them.

Our measurement approach relates to the forecast-error-on-revision regressions of Coibion and Gorodnichenko (2015). This literature uses the sign of predictable forecast errors to study under- and over-reaction to information. We build on this elegant framework by removing analyst-specific biases and updating tendencies and focusing on the *absolute* pre-

dictable error associated with each firm. Thus, the direction of the updating error is not relevant for our purpose, nor is the consensus revision: instead, larger absolute predictable errors for the same forecasters reveal greater firm complexity.

Our findings speak to several literatures across finance and economics. First, we contribute to the literature on firm complexity and information processing. Prior work includes Cohen and Lou (2012) and Peters and Taylor (2017). Our contribution is to measure firm complexity directly from the systematic difficulties experienced by professional analysts, rather than assigning complexity based on observable firm characteristics or researcher-defined informational relationships. This provides a revealed, firm-level measure of the difficulty of interpreting information about fundamentals.

Second, we relate to the literature on belief formation and expectation errors. Bouchaud et al. (2019) find that sticky expectations contribute to the profitability anomaly, while Bordalo et al. (2019) show how diagnostic expectations generate overreaction to information and predictable returns. More broadly, this literature documents systematic departures from rational expectations and studies their implications for financial markets. We contribute by shifting attention from agent's biases to the complexity of the object being forecast, after removing analyst-specific biases.

Third, we contribute to the literature on cross-sectional return predictability and the amplification of asset-pricing anomalies. Prior work documents identifies limits to arbitrage that can exacerbate mispricing (Stambaugh and Yuan, 2017), and organizes the large cross-section of documented anomalies into economically related themes (Jensen, Kelly and Pedersen, 2023). We show that revealed firm complexity is associated with stronger profitability and quality anomalies, even after controlling for size and idiosyncratic volatility. Importantly, these anomalies are concentrated among firms that are most difficult for professional forecasters to understand, rather than being uniformly present across firms. These findings are consistent with difficulties in interpreting firm fundamentals contributing to the cross-section of predictable returns.

Fourth, the paper contributes to a growing literature on complexity in economic decision making (Puri (2024), Oprea (2024), Agranov, Schotter and Trevino (2026); among many others). This literature develops theories of complexity and finds experimentally that harder problems generate greater cognitive costs, aversion, and mistakes. Some experimental papers use behavior such as decision time (Agranov, Schotter and Trevino, 2026) or matched mathematical mistakes (Enke and Shubatt, 2026), to measure complexity. In the laboratory, however, the researcher designs the task, controls the information set, and knows the correct solution. Measuring complexity in real-world settings requires a different approach. We use repeated forecasts by the same professionals across firms to separate forecaster-specific

mistakes from mistakes systematically associated with the firm. This yields a revealed measure of firm complexity, which we then show is reflected in market prices. In this sense, the paper connects the emerging economics of complexity to real-world expectation formation and pricing.

More broadly, the results connect two central questions in economics: when departures from full-information belief formation arise, and whether those departures are reflected in equilibrium prices. Professional analysts operate in a setting with strong incentives, repeated opportunities to learn, and unusually rich information. Yet the same experts make systematically different updating mistakes across the firms they cover, and those differences predict where fundamentals-based return anomalies are strongest. Our results therefore suggest that predictable returns are partly organized by the difficulty of forming correct beliefs.

The paper proceeds as follows. Section 2 introduces the revealed complexity measure and its construction. Section 3 studies how complexity amplifies anomalies, and its organizing role.

2 Revealed Complexity Measure

2.1 Thought Experiment

We use the following thought experiment. Consider the same person updating about two different firms. He makes more predictable mistakes for one firm than the other. We call the firm on which his forecast revision leaves a larger absolute predictable mistake, revealed complex.

2.2 Empirical Specification

To implement the thought experiment, we use analyst-level forecasts and revisions. Observing individual analysts allows us to separate systematic differences across analysts from systematic differences across firms. Let i index firms, y fiscal targets, j analysts, t revision dates, and q rolling-window quarters. Given the forecast revision $r_{i,y,j,t}$ and subsequent forecast errors $e_{i,y,j,t}$ (whose construction we detail in the next section), we estimate within each rolling window q,

$$e_{i,y,t,j} = \alpha_{i,q} + \gamma_{j,q} + (\beta_{i,q} + \delta_{j,q})\, r_{i,y,t,j} + \epsilon_{i,y,t,j}.$$

The analyst fixed effect $\gamma_{j,q}$ absorbs analyst j's general tendency to forecast too high or too low, and the analyst slope $\delta j, q$ captures his general tendency to over- or under-

react to information. The firm intercept $\alpha_{i,q}$ captures persistent forecast bias for firm i, and the firm-slope $\beta_{i,q}$ captures how strongly revisions for firm i predict the forecast error that remains. Following the literature's practice for rolling analysis using analyst revisions (Dessaint, Foucault and Fresard, 2024; Bouchaud et al., 2019; De Silva and Thesmar, 2024), we estimate all coefficients jointly by ordinary least squares within each rolling window.[1]

We now observe that – conditional on having enough variation for each firm and analyst – the above system contains, for every window q, an intercept and a slope for each of the F firms and each of the A analysts: $2F + 2A$ coefficients in total. Not all of them are separately identified. Every observation belongs to one firm and one analyst, so the data reveal only the sums $\alpha_{i,q} + \gamma_{j,q}$ and $\beta_{i,q} + \delta_{j,q}$ for firm–analyst pairs observed in the sample. Within any connected component of the firm–analyst coverage network, adding a common constant to all firm intercepts and subtracting it from all analyst intercepts leaves every fitted value unchanged; the same holds for the slopes. Let C_q denote the number of connected components in window q. There are therefore two unidentified directions per connected component, or $2C_q$ in total, so the data provide $2F_q + 2A_q - 2C_q$ independent restrictions on the $2F_q + 2A_q$ coefficients.

To add the equations required for identification, we require that the average analyst fixed effect and the average analyst slope equals zero within each connected component. As a result, the firm-level fixed effect and slope represent failures to update above and beyond analysts' typical failure to update in the sample, mapping back to the motivating thought experiment of Section 2.1. Formally we require $\sum n_{j,q}\gamma_{j,q} = 0$ and $\sum n_{j,q}\delta_{j,q} = 0$, where $n_{j,q}$ is the number of revisions by analyst j in rolling window q for any firm.

We define *Firm-Specific Predictable Error Complexity* (F-SPEC) as the magnitude of this firm-specific forecast-error-on-revision coefficient:

$$\text{F-SPEC}_{i,q} = \left|\hat{\beta}_{i,q}\right|.$$

We take absolute values because complexity reflects the size, not the direction, of predictable forecast errors. Without them, offsetting positive and negative errors could make a difficult firm appear easy: in our thought experiment, any deviation from the objectively correct update, no matter its direction, reflects revealed failure to update. Zero therefore means no firm-specific predictable updating error, while larger values indicate greater revealed complexity. Because both revisions and forecast errors are normalized by the same price measure, F-SPEC is unitless.

[1]Note that since the complexity measure relies on point estimates, the type of standard errors used do not affect the complexity measure.

2.3 Data and Cleaning

Data on analyst forecasts and realized earnings come from the I/B/E/S Unadjusted Detail and Unadjusted Actuals files, respectively. We pull all individual analysts' annual EPS forecasts for ordinary common shares of U.S.-incorporated companies. The forecast sample covers announcements from January 1984 through December 2024. We match each forecast to its realization from the Unadjusted Actuals file. Data on stock prices, security classifications, and cumulative share-adjustment factors come from the CRSP daily stock file. Data on firm characteristics and factors come from the Global Factor Data of Jensen, Kelly and Pedersen (2023).

We follow the literature in cleaning the I/B/E/S data and constructing forecast revisions (Clement and Tse, 2005; Bouchaud et al., 2019; De Silva and Thesmar, 2024; Jensen, Kelly and Pedersen, 2023). We define a revision pair as two consecutive EPS forecasts by the same analyst for the same firm and fiscal-period end date. Forecasts are ordered by announcement date and time, and each forecast is paired with the analyst's immediately preceding forecast. The two forecasts must occur on different calendar days, and each must strictly precede the report date of the realized annual EPS.[2]

We use CRSP cumulative share-adjustment factors to express the old forecast, the new forecast, realized EPS, and the normalization price on a common split-adjusted share basis, dividing each per-share quantity by the cumulative factor in effect on its own measurement date. Following Clement and Tse (2005), the normalization price is the CRSP price from the second trading day preceding the new forecast, adjusted using the share factor applying on that trading day.[3] For firm i, analyst j, fiscal-year target y, and new-forecast date t, we define the price-scaled revision and the subsequent realized forecast error as

$$r_{i,t,y,j} \;=\; \frac{F^{adj}_{new,i,t,y,j} - F^{adj}_{old,i,t,y,j}}{P^{adj}_{i,t-2}}, \qquad e_{i,t,y,j} \;=\; \frac{A^{adj}_{i,y} - F^{adj}_{new,i,t,y,j}}{P^{adj}_{i,t-2}}, \tag{1}$$

where $F^{adj}_{new,i,t,y,j}$ and $F^{adj}_{old,i,t,y,j}$ are the split-adjusted new and immediately preceding forecasts, $A^{adj}_{i,y}$ is split-adjusted realized annual EPS, and $P^{adj}_{i,t-2}$ is the split-adjusted stock price two trading days before the new forecast. Thus, $r_{i,t,y,j} > 0$ denotes an upward forecast revision, while $e_{i,t,y,j} > 0$ indicates that realized EPS exceeded the analyst's new forecast.

To implement the complexity measure of Section 2.2, we use a rolling window length

[2]This procedure follows Ivkovic and Jegadeesh (2004) and Clement and Tse (2005) in retaining all chronologically valid forecast revisions; useful for our exercise because our object of interest is the analyst- and firm-level relation between the forecast revision and the subsequently realized error, retaining all valid revisions helps maximize power.

[3]They, and we, use the price two trading days before the new forecast so that the normalization price is not affected by information released with the forecast revision.

of 12 months. To prevent look-ahead bias, we use only forecast revisions and subsequent forecast errors that are observable by the end of each rolling window. To help ensure enough variation to estimate intercepts and slopes, we follow prior literature on rolling analyst revisions Bordalo et al. (2019); Dessaint, Foucault and Fresard (2024) in imposing minimum observation requirements: we require at least 20 observations per firm and 5 per analyst within the window for inclusion; this requirement retains 64% of revisions.

3 Revealed Firm Complexity and Factor Amplification

Intuitively, revealed firm complexity is defined by experts not being able to map theoretically known information to firm fundamentals. This implies that the mental model of the firm is harder to fully understand. As a result, fundamental performance-based factors, such as profitability or quality, may be exacerbated in more complex firms. We test this prediction here.

Tested against the zoo of 153 factors documented in the literature, we find that complexity exacerbates profitability and quality in all specifications. In particular complexity amplifies these anomalies in raw double sorts, as well as in triple sorts that additionally control for size and for idiosyncratic volatility. Complexity further exacerbates momentum and low risk factors after controlling for size or for idiosyncratic volatility.

3.1 Data and Portfolio Construction

We use the 153 global factor database of Jensen, Kelly and Pedersen (2023) (henceforth JKP), who collate and construct all factors found in the finance literature into a readily accessible database. We match each stock-month to the most recent quarterly observation of revealed complexity. The matched sample contains 267,858 stock-months from 5,829 firms.

Each month, we sort firms into low-, middle-, and high-complexity groups using the 30th and 70th percentile breakpoints of complexity estimated from NYSE firms. We independently sort firms on each anomaly characteristic using monthly 30th and 70th percentile breakpoints estimated from NYSE firms. For anomaly k, complexity tercile c, ad month t, let $R^{H,c}_{k,t}$ and $R^{L,c}_{k,t}$ denote the value-weighted one-month-ahead excess returns of the high and low characteristic portfolios. The high-characteristic portfolio contains firms at or above the monthly NYSE 70th-percentile characteristic breakpoint, while the low-characteristic portfolio contains firms at or below the monthly NYSE 30th-percentile breakpoint; these breakpoints are common across complexity groups.[4]

[4]These percentiles breaks and independent sorts within portfolios follow Fama and French (1993), **?**, and

We orient each anomaly in the direction reported by JKP. Let $d_k \in \{-1, 1\}$ denote the direction indicator. If $d_k = 1$, the documented anomaly return is high minus low; if -1, low minus high. We define $A^c_{k,t+1} \coloneqq d_k \left(R^{H,c}_{k,t+1} - R^{L,c}_{k,t+1} \right)$. This normalization gives every anomaly sort the same directional interpretation: a positive $A^c_{k,t+1}$ means the anomaly earns a positive return in its documented direction.

Our object of interest is:

$$\text{Complexity Amplification for Anomaly } k \text{ in month } t \coloneqq \Delta A_{k,t} \coloneqq A^3_{k,t+1} - A^1_{k,t+1},$$

where groups 1 and 3 contain the least and most complex firms, respectively. A positive $\Delta A_{k,t+1}$ means that the anomaly is stronger among high-complexity firms. We call this amplification.

We next check, for robustness, whether this relation survives conditioning on size or idiosyncratic volatility, characteristics known to amplify anomalies in general (Fama and French, 2008). For each control variable, we first sort firms each month into three control portfolios using the 33rd and 67th percentile breakpoints estimated from NYSE firms (Fama and French, 1993). We measure size as market equity and idiosyncratic volatility as the 21-day Fama–French three-factor idiosyncratic volatility measure (Ang et al., 2006). Within each control tercile, we independently sort firms on complexity and on the anomaly characteristic using NYSE breakpoints, following the independent portfolio-sort methodology of Fama and French (1993) and Stambaugh and Yuan (2017). Specifically, we form low-, middle-, and high-complexity groups using the 30th and 70th percentile breakpoints of complexity estimated from NYSE firms within that control tercile. We separately estimate the anomaly characteristic's 30th and 70th percentile breakpoints using NYSE firms within the same control tercile and apply those same breakpoints across all three complexity groups. Thus, conditional on the control tercile, the complexity and anomaly-characteristic sorts are independent. For each complexity group, we then equal-weight the corresponding anomaly returns across the three control terciles, as in characteristic-controlled portfolio sorts such as Ang et al. (2006), and retain the month only when all three control terciles contribute. Because the control characteristic is excluded from the anomaly set, the size-controlled specification excludes market equity and the idiosyncratic-volatility-controlled specification excludes the 21-day Fama–French three-factor idiosyncratic-volatility characteristic, leaving 152 anomalies in each controlled specification.

For each of: the complexity sort; the size-then-complexity sort; and the idiosyncratic volatility-then-complexity sort, we report the mean excess return amplification $\Delta A_{k,t+1}$

Stambaugh and Yuan (2017).

and its corresponding CAPM alpha α_k^{Δ}, estimated the usual way (Ang et al., 2006) as $\Delta A_{k,t+1} = \alpha_k^{\Delta} + \beta_k R_{t+1}^{MKT} + u_{k,t+1}$, with R_t^{MKT} the excess market return and $u_{k,t}$ a noise term. Following JKP, we require at least five stocks in each characteristic leg of each double or triple-sorted portfolio. Inference throughout uses Newey-West heteroskedasticity and autocorrelation robust standard errors.

3.2 Complexity Amplifies Profitability and Quality Anomalies

Complexity amplifies a broad set of anomalies. In the baseline complexity specification, 105 of 153 anomalies (68.6 percent) have positive CAPM amplification alphas, of which 13 are statistically significant at the 5 percent level. Conditioning on size yields positive alphas for 99 of 152 anomalies (65.1 percent), with 19 significant at the 5 percent level. Conditioning on idiosyncratic volatility yields positive alphas for 90 of 152 anomalies (59.2 percent), with 20 significant at the 5 percent level.

Table 3.1 aggregates the anomaly returns using the factor themes defined by JKP. Profitability and quality are the only themes with positive and statistically significant amplification in all three specifications. The CAPM alpha for profitability is 0.41 percent per month in the Raw Complexity specification, 0.33 percent after controlling for size, and 0.51 percent after controlling for idiosyncratic volatility. The corresponding estimates for Quality are 0.40, 0.39, and 0.45 percent per month. After controlling for size or idiosyncratic volatility, momentum and low risk also exhibit positive and marginally statistically significant amplification. The remaining themes yield smaller and generally statistically insignificant estimates.

Figure 3.1 decomposes each factor theme's excess returns by complexity tercile. Figure 3.2 does the same for each factor theme's CAPM alphas. Profitability and quality anomalies are not statistically distinguishable from zero in the lowest complexity tercile. They arise only in the highest complexity firms. The absence of these anomalies for low complexity firms are consistent with profitability and quality anomalies being mispricing-, rather than risk-based. The momentum and low risk themes show higher factor returns in the high complexity portfolio than the low- and medium- portfolios, but are not statistically significant in the complexity double sort; as Table 3.1 shows, low risk becomes significant only after controlling for size or for idiosyncratic volatility, and momentum after controlling for size.

One way to organize results across themes is that complexity appears to matter more for performance-related signals than for other sources of predictability. Reinforcing this interpretation, after controlling for size, the Stambaugh and Yuan (2017) performance composite factor the CAPM alpha complexity amplification is 0.31% ($p = 0.051$) per monthly and

raw complexity amplification is 0.35% ($p < 0.01$). After controlling for idiosyncratic volatility, the performance composite factor has CAPM alpha complexity amplification of 0.62% ($p < 0.05$) and raw complexity amplification of 0.71% ($p < 0.01$).

TABLE 3.1: Complexity Amplification Portfolios Across Factor Themes

	Complexity		Size → Complexity		IVOL → Complexity	
	Excess Return	CAPM Alpha	Excess Return	CAPM Alpha	Excess Return	CAPM Alpha
Profitability	0.46**	0.41**	0.35***	0.33***	0.51***	0.51***
	(0.19)	(0.19)	(0.12)	(0.12)	(0.17)	(0.18)
Quality	0.45**	0.40**	0.43***	0.39***	0.49***	0.45***
	(0.20)	(0.19)	(0.14)	(0.14)	(0.16)	(0.16)
Momentum	0.15	0.25	0.43***	0.46***	0.30	0.33*
	(0.23)	(0.23)	(0.16)	(0.17)	(0.19)	(0.19)
Low Risk	0.17	0.11	0.33**	0.31*	0.49***	0.44***
	(0.20)	(0.20)	(0.16)	(0.16)	(0.16)	(0.16)
Low Leverage	0.21	0.23	0.02	0.03	0.22	0.22
	(0.19)	(0.19)	(0.15)	(0.14)	(0.14)	(0.14)
Profit Growth	0.15	0.17	−0.15	−0.17	−0.02	−0.03
	(0.15)	(0.14)	(0.12)	(0.13)	(0.13)	(0.13)
Debt Issuance	0.11	0.15	−0.09	−0.09	−0.18	−0.21*
	(0.18)	(0.18)	(0.11)	(0.11)	(0.12)	(0.12)
Value	0.08	0.07	0.06	0.07	−0.04	−0.04
	(0.18)	(0.18)	(0.12)	(0.12)	(0.16)	(0.16)
Accruals	0.04	0.03	−0.08	−0.09	0.05	−0.01
	(0.21)	(0.21)	(0.13)	(0.13)	(0.18)	(0.17)
Investment	−0.04	0.00	−0.19	−0.13	−0.07	−0.03
	(0.21)	(0.21)	(0.14)	(0.15)	(0.16)	(0.17)
Short-Term Reversal	−0.03	−0.01	−0.17	−0.18	−0.02	0.01
	(0.25)	(0.23)	(0.13)	(0.13)	(0.15)	(0.15)
Size	−0.21	−0.05	0.07	0.05	−0.13	−0.08
	(0.25)	(0.25)	(0.11)	(0.11)	(0.14)	(0.15)
Seasonality	−0.17	−0.17	−0.04	−0.02	0.18*	0.18*
	(0.20)	(0.19)	(0.08)	(0.08)	(0.10)	(0.11)

Notes: This table reports mean excess returns and CAPM alphas of complexity-amplification portfolios, in percent per month. For each anomaly, the amplification portfolio is long the JKP anomaly portfolio among high-complexity firms and short the corresponding anomaly portfolio among low-complexity firms. Anomaly returns are equal-weighted across factors within each JKP theme each month. The Excess Return columns report the mean return on this portfolio, while the CAPM Alpha columns report the intercept from a regression of the same monthly portfolio return on the market excess return. Complexity denotes the independent complexity-characteristic sort. Size → Complexity and IVOL → Complexity first condition on size or idiosyncratic volatility, respectively, before forming the complexity-amplification portfolios. Newey-West HAC standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

FIGURE 3.1: Factor Excess Returns Within Complexity Terciles

Notes: This figure reports monthly factor excess returns for JKP themes in each of the low-, middle-, and high-complexity firms. Points estimates and 95% confidence intervals are shown. Panel (a) reports the results in the complexity double sort, Panel (b) in the triple sort that conditions first on size, and Panel (c) in the triple sort that conditions first on idiosyncratic volatility. Profitability, quality, momentum, and low risk are shown first, followed by the remaining JKP themes in alphabetical order.

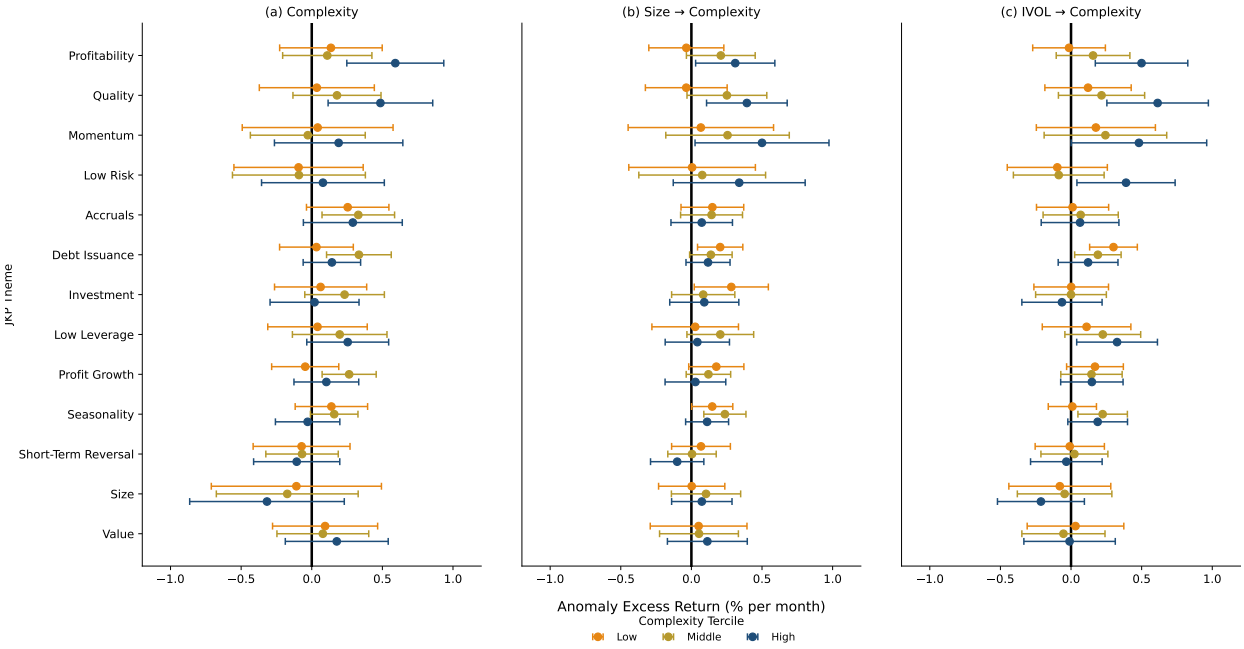
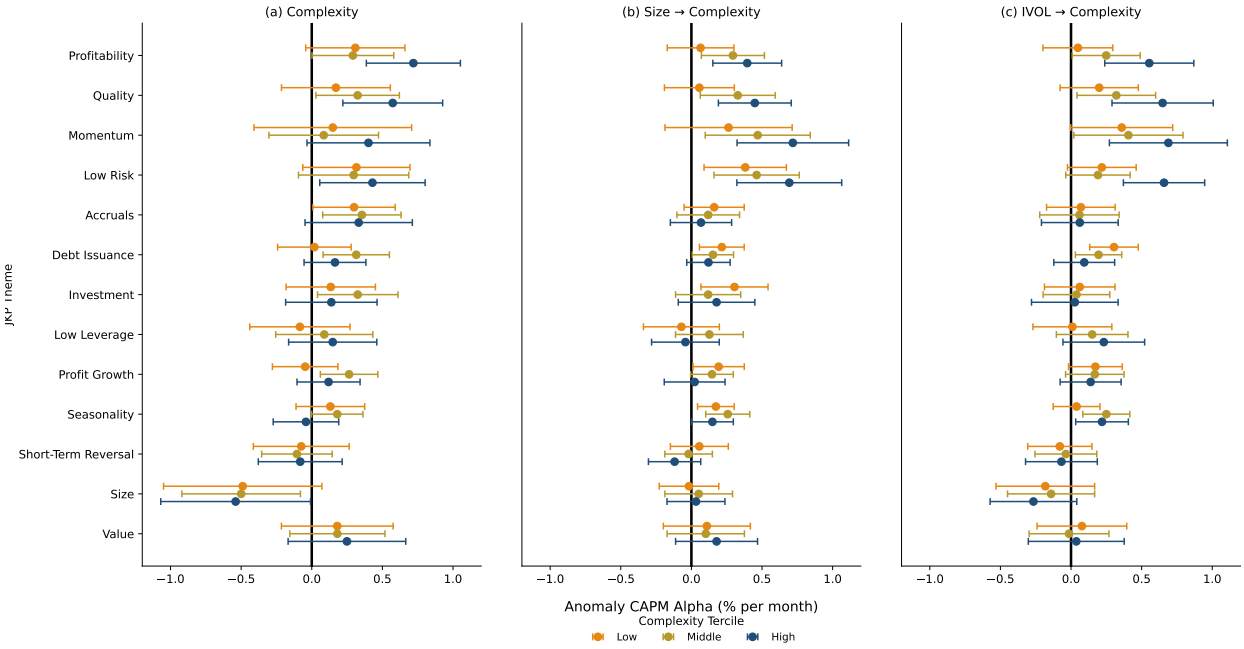


FIGURE 3.2: Factor CAPM Alpha Within Complexity Terciles

Notes: This figure reports monthly factor CAPM alphas for JKP themes in each of the low-, middle-, and high-complexity firms. Points estimates and 95% confidence intervals are shown. Panel (a) reports the results in the complexity double sort, Panel (b) in the triple sort that conditions first on size, and Panel (c) in the triple sort that conditions first on idiosyncratic volatility. Profitability, quality, momentum, and low risk are shown first, followed by the remaining JKP themes in alphabetical order.



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A Complexity and Factor Amplification: Appendix

A.1 All Factors

Table A.1 reports factor-level results for complexity amplification, with factors organized alphabetically. Table A.2 reports the largest individual amplification alphas under each specification.

TABLE A.1: Factor-Level Complexity Amplification

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Abnormal corporate investment	capex_abn	Debt Issuance	−0.28	−0.22	−0.46**
			(0.32)	(0.21)	(0.23)
Altman Z-score	z_score	Low Leverage	0.56**	0.40**	0.82***
			(0.29)	(0.19)	(0.22)
Amihud Measure	ami_126d	Size	0.43	0.17	0.11
			(0.50)	(0.14)	(0.19)
Asset Growth	at_gr1	Investment	0.08	−0.04	−0.16
			(0.30)	(0.21)	(0.26)
Asset tangibility	tangibility	Low Leverage	0.65**	0.12	0.47*
			(0.32)	(0.20)	(0.28)
Asset turnover	sale_bev	Quality	0.25	0.36*	0.53**
			(0.27)	(0.21)	(0.25)
Assets-to-market	at_me	Value	−0.19	−0.14	−0.45*
			(0.25)	(0.21)	(0.25)
Book leverage	at_be	Low Leverage	0.57*	0.24	0.47*
			(0.31)	(0.18)	(0.25)
Book-to-market enterprise value	bev_mev	Value	−0.50	−0.17	−0.47**
			(0.31)	(0.21)	(0.22)
Book-to-market equity	be_me	Value	−0.23	0.14	−0.11
			(0.31)	(0.20)	(0.24)
CAPEX growth (1 year)	capx_gr1	Investment	0.16	−0.12	−0.05
			(0.33)	(0.20)	(0.24)
CAPEX growth (2 years)	capx_gr2	Investment	−0.05	−0.13	−0.20
			(0.33)	(0.20)	(0.28)
CAPEX growth (3 years)	capx_gr3	Investment	−0.20	0.06	−0.17
			(0.30)	(0.24)	(0.30)
Capital turnover	at_turnover	Quality	0.35	0.26	0.45*
			(0.28)	(0.19)	(0.23)
Cash flow volatility	ocfq_saleq_std	Low Risk	0.41	0.20	0.43**
			(0.28)	(0.16)	(0.21)
Cash-based operating profits-to-book assets	cop_at	Quality	0.30	0.31*	0.53**
			(0.23)	(0.17)	(0.23)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Cash-based operating profits-to-lagged book assets	cop_atl1	Quality	0.53**	0.34*	0.58***
			(0.23)	(0.19)	(0.21)
Cash-to-assets	cash_at	Low Leverage	0.05	0.41**	0.12
			(0.24)	(0.20)	(0.23)
Change gross margin minus change sales	dgp_dsale	Quality	0.15	0.04	−0.29
			(0.33)	(0.19)	(0.26)
Change in common equity	be_gr1a	Investment	−0.33	−0.18	−0.19
			(0.31)	(0.21)	(0.23)
Change in current operating assets	coa_gr1a	Investment	0.35	0.47***	0.36*
			(0.30)	(0.17)	(0.21)
Change in current operating liabilities	col_gr1a	Investment	0.10	0.24	−0.03
			(0.32)	(0.18)	(0.29)
Change in current operating working capital	cowc_gr1a	Accruals	0.12	0.24	0.23
			(0.29)	(0.18)	(0.25)
Change in financial liabilities	fnl_gr1a	Debt Issuance	0.04	−0.05	−0.27
			(0.30)	(0.17)	(0.22)
Change in long-term investments	lti_gr1a	Seasonality	0.18	0.66	0.29
			(0.28)	(0.43)	(0.39)
Change in long-term net operating assets	lnoa_gr1a	Investment	0.16	0.05	−0.16
			(0.29)	(0.21)	(0.27)
Change in net financial assets	nfna_gr1a	Debt Issuance	−0.59**	−0.13	−0.24
			(0.29)	(0.16)	(0.23)
Change in net noncurrent operating assets	nncoa_gr1a	Investment	0.06	−0.35	−0.65**
			(0.32)	(0.27)	(0.29)
Change in net operating assets	noa_gr1a	Investment	−0.27	−0.34	−0.41
			(0.29)	(0.21)	(0.26)
Change in noncurrent operating assets	ncoa_gr1a	Investment	0.08	−0.19	−0.44
			(0.31)	(0.24)	(0.32)
Change in noncurrent operating liabilities	ncol_gr1a	Debt Issuance	−0.02	−0.06	−0.28
			(0.30)	(0.21)	(0.25)
Change in operating cash flow to assets	ocf_at_chg1	Profit Growth	−0.13	−0.06	−0.20
			(0.33)	(0.20)	(0.27)
Change in quarterly return on assets	niq_at_chg1	Profit Growth	−0.17	−0.24	−0.27
			(0.29)	(0.22)	(0.24)
Change in quarterly return on equity	niq_be_chg1	Profit Growth	−0.31	−0.05	−0.22
			(0.31)	(0.24)	(0.28)
Change in short-term investments	sti_gr1a	Seasonality	−0.56	0.38	0.36
			(0.41)	(0.26)	(0.40)
Change PPE and Inventory	ppeinv_gr1a	Investment	−0.13	0.11	−0.41
			(0.28)	(0.21)	(0.29)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Change sales minus change Inventory	dsale_dinv	Profit Growth	0.51*	−0.28	−0.07
			(0.29)	(0.20)	(0.26)
Change sales minus change receivables	dsale_drec	Profit Growth	0.32	−0.09	0.03
			(0.32)	(0.19)	(0.27)
Change sales minus change SG&A	dsale_dsga	Profit Growth	0.17	−0.18	−0.29
			(0.29)	(0.25)	(0.30)
Coefficient of variation for dollar trading volume	dolvol_var_126d	Profitability	0.27	0.54***	0.34
			(0.30)	(0.18)	(0.23)
Coefficient of variation for share turnover	turnover_var_126d	Profitability	0.21	0.35*	0.44*
			(0.30)	(0.18)	(0.23)
Coskewness	coskew_21d	Seasonality	−0.24	−0.06	−0.47**
			(0.31)	(0.15)	(0.22)
Current price to high price over last year	prc_highprc_252d	Momentum	0.43	0.25	0.50**
			(0.29)	(0.17)	(0.24)
Debt-to-market	debt_me	Value	−0.30	−0.18	−0.65**
			(0.29)	(0.20)	(0.25)
Dimson beta	beta_dimson_21d	Low Risk	−0.11	0.19	0.57***
			(0.31)	(0.18)	(0.21)
Dividend yield	div12m_me	Value	0.50*	0.16	0.13
			(0.29)	(0.21)	(0.26)
Dollar trading volume	dolvol_126d	Size	−0.03	0.26*	0.23
			(0.34)	(0.15)	(0.16)
Downside beta	betadown_252d	Low Risk	0.51*	0.20	0.53**
			(0.29)	(0.19)	(0.23)
Earnings persistence	ni_ar1	Debt Issuance	−0.03	−0.11	−0.16
			(0.29)	(0.19)	(0.24)
Earnings variability	earnings_variability	Low Risk	−0.55*	−0.12	−0.18
			(0.29)	(0.18)	(0.24)
Earnings volatility	ni_ivol	Low Leverage	0.13	0.11	−0.22
			(0.31)	(0.21)	(0.25)
Earnings-to-price	ni_me	Value	0.31	0.27	0.30
			(0.28)	(0.19)	(0.27)
Ebitda-to-market enterprise value	ebitda_mev	Value	0.13	0.32*	0.24
			(0.28)	(0.17)	(0.23)
Equity duration	eq_dur	Value	−0.14	0.20	0.18
			(0.33)	(0.19)	(0.25)
Equity net payout	eqnpo_12m	Value	0.04	0.11	0.22
			(0.27)	(0.17)	(0.22)
Firm age	age	Low Leverage	−0.30	−0.29	0.01
			(0.24)	(0.22)	(0.22)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Frazzini-Pedersen market beta	betabab_1260d	Low Risk	0.48*	0.50**	0.90***
			(0.28)	(0.21)	(0.25)
Free cash flow-to-price	fcf_me	Value	0.25	0.08	−0.20
			(0.33)	(0.24)	(0.24)
Gross profits-to-assets	gp_at	Quality	0.06	0.08	0.32
			(0.26)	(0.18)	(0.24)
Gross profits-to-lagged assets	gp_atl1	Quality	0.44*	0.15	0.40*
			(0.26)	(0.19)	(0.23)
Growth in book debt (3 years)	debt_gr3	Debt Issuance	0.46	0.06	−0.14
			(0.29)	(0.19)	(0.28)
Highest 5 days of return	rmax5_21d	Low Risk	0.24	0.26	0.33
			(0.30)	(0.26)	(0.27)
Highest 5 days of return scaled by volatility	rmax5_rvol_21d	Short-Term Reversal	−0.00	0.09	−0.09
			(0.27)	(0.18)	(0.20)
Hiring rate	emp_gr1	Investment	0.36	0.17	0.34
			(0.32)	(0.21)	(0.28)
Idiosyncratic skewness from the CAPM	iskew_capm_21d	Short-Term Reversal	0.05	−0.27	0.12
			(0.27)	(0.18)	(0.22)
Idiosyncratic skewness from the Fama-French 3-factor model	iskew_ff3_21d	Short-Term Reversal	−0.14	−0.31	−0.02
			(0.28)	(0.19)	(0.22)
Idiosyncratic skewness from the q-factor model	iskew_hxz4_21d	Short-Term Reversal	−0.19	−0.30	0.07
			(0.27)	(0.18)	(0.25)
Idiosyncratic volatility from the CAPM (21 days)	ivol_capm_21d	Low Risk	0.22	0.10	−0.05
			(0.34)	(0.25)	(0.21)
Idiosyncratic volatility from the CAPM (252 days)	ivol_capm_252d	Low Risk	0.82**	0.23	0.63*
			(0.36)	(0.23)	(0.33)
Idiosyncratic volatility from the Fama-French 3-factor model	ivol_ff3_21d	Low Risk	0.28	0.14	–
			(0.31)	(0.24)	
Idiosyncratic volatility from the q-factor model	ivol_hxz4_21d	Low Risk	0.15	0.14	−0.11
			(0.29)	(0.22)	(0.21)
Intrinsic value-to-market	ival_me	Value	−0.13	0.24	−0.13
			(0.26)	(0.20)	(0.23)
Inventory change	inv_gr1a	Investment	0.38	0.10	0.39*
			(0.25)	(0.16)	(0.21)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Inventory growth	inv_gr1	Investment	0.24	0.04	0.39
			(0.32)	(0.18)	(0.27)
Kaplan-Zingales index	kz_index	Seasonality	−0.30	−0.29	0.19
			(0.33)	(0.20)	(0.29)
Labor force efficiency	sale_emp_gr1	Profit Growth	0.54*	0.03	−0.04
			(0.30)	(0.18)	(0.29)
Liquidity of book assets	aliq_at	Investment	0.11	−0.24	−0.18
			(0.34)	(0.17)	(0.23)
Liquidity of market assets	aliq_mat	Low Leverage	0.15	−0.15	0.46**
			(0.29)	(0.21)	(0.22)
Long-term reversal	ret_60_12	Investment	−0.19	−0.06	−0.04
			(0.32)	(0.23)	(0.27)
Market Beta	beta_60m	Low Risk	0.60**	0.63***	0.56**
			(0.30)	(0.22)	(0.28)
Market correlation	corr_1260d	Seasonality	0.34	0.23	0.38*
			(0.25)	(0.16)	(0.20)
Market Equity	market_equity	Size	0.16	–	−0.01
			(0.40)		(0.20)
Maximum daily return	rmax1_21d	Low Risk	0.29	0.28	0.27
			(0.27)	(0.23)	(0.22)
Mispricing factor: Management	mispricing_mgmt	Investment	0.10	0.03	0.01
			(0.26)	(0.23)	(0.23)
Mispricing factor: Performance	mispricing_perf	Quality	0.38	0.31*	0.62**
			(0.30)	(0.16)	(0.25)
Net debt issuance	dbnetis_at	Seasonality	−0.02	−0.12	−0.33
			(0.29)	(0.18)	(0.22)
Net debt-to-price	netdebt_me	Low Leverage	0.21	0.24	0.46*
			(0.29)	(0.21)	(0.26)
Net equity issuance	eqnetis_at	Value	0.56*	0.12	0.31
			(0.30)	(0.17)	(0.25)
Net operating assets	noa_at	Debt Issuance	0.15	0.06	−0.15
			(0.27)	(0.22)	(0.23)
Net payout yield	eqnpo_me	Value	0.08	0.12	0.26
			(0.30)	(0.22)	(0.28)
Net stock issues	chcsho_12m	Value	0.26	0.06	0.09
			(0.28)	(0.20)	(0.20)
Net total issuance	netis_at	Value	0.33	0.03	−0.42**
			(0.32)	(0.17)	(0.21)
Number of consecutive quarters with earnings increases	ni_inc8q	Quality	0.31	0.07	0.12
			(0.24)	(0.17)	(0.21)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Number of zero trades with turnover as tiebreaker (1 month)	zero_trades_21d	Low Risk	0.50*	0.34*	0.40
			(0.27)	(0.18)	(0.26)
Number of zero trades with turnover as tiebreaker (12 months)	zero_trades_252d	Low Risk	0.60**	0.27	0.32
			(0.29)	(0.20)	(0.30)
Number of zero trades with turnover as tiebreaker (6 months)	zero_trades_126d	Low Risk	0.47	0.35**	0.44
			(0.30)	(0.18)	(0.29)
Ohlson O-score	o_score	Profitability	0.33	0.43**	0.18
			(0.36)	(0.17)	(0.20)
Operating accruals	oaccruals_at	Accruals	−0.27	−0.18	−0.10
			(0.31)	(0.20)	(0.21)
Operating cash flow to assets	ocf_at	Profitability	0.48*	0.24	0.52**
			(0.25)	(0.17)	(0.23)
Operating cash flow-to-market	ocf_me	Value	0.02	−0.12	−0.35
			(0.32)	(0.20)	(0.26)
Operating leverage	opex_at	Quality	−0.17	0.08	0.27
			(0.30)	(0.22)	(0.23)
Operating profits-to-book assets	op_at	Quality	0.56**	0.24	0.73***
			(0.23)	(0.19)	(0.23)
Operating profits-to-book equity	ope_be	Profitability	0.73**	0.05	0.37
			(0.31)	(0.21)	(0.27)
Operating profits-to-lagged book assets	op_atl1	Quality	0.53*	0.46**	0.64***
			(0.30)	(0.20)	(0.22)
Operating profits-to-lagged book equity	ope_bel1	Profitability	0.48	0.17	0.48*
			(0.30)	(0.21)	(0.26)
Payout yield	eqpo_me	Value	0.13	0.00	−0.06
			(0.30)	(0.19)	(0.29)
Percent operating accruals	oaccruals_ni	Accruals	−0.15	−0.33	−0.51*
			(0.35)	(0.20)	(0.27)
Percent total accruals	taccruals_ni	Accruals	0.09	−0.15	−0.36
			(0.31)	(0.17)	(0.27)
Pitroski F-score	f_score	Profitability	0.44*	0.40**	0.30
			(0.24)	(0.16)	(0.22)
Price momentum t-12 to t-1	ret_12_1	Momentum	0.09	0.23	0.23
			(0.27)	(0.19)	(0.28)
Price momentum t-12 to t-7	ret_12_7	Profit Growth	0.02	−0.01	0.10
			(0.31)	(0.19)	(0.27)
Price momentum t-3 to t-1	ret_3_1	Momentum	0.19	0.22	−0.10
			(0.28)	(0.17)	(0.24)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Price momentum t-6 to t-1	ret_6_1	Momentum	0.07	0.42**	0.32
			(0.34)	(0.21)	(0.28)
Price momentum t-9 to t-1	ret_9_1	Momentum	0.24	0.35*	0.41*
			(0.29)	(0.18)	(0.24)
Price per share	prc	Size	−0.76**	−0.31	−0.55**
			(0.36)	(0.20)	(0.23)
Profit margin	ebit_sale	Profitability	0.56*	0.24	0.22
			(0.30)	(0.20)	(0.24)
Quality minus Junk: Composite	qmj	Quality	0.95***	0.15	0.51**
			(0.28)	(0.17)	(0.23)
Quality minus Junk: Growth	qmj_growth	Quality	0.06	−0.18	0.02
			(0.27)	(0.22)	(0.27)
Quality minus Junk: Profitability	qmj_prof	Quality	0.18	0.36**	0.48**
			(0.28)	(0.17)	(0.21)
Quality minus Junk: Safety	qmj_safety	Quality	0.97***	0.56***	0.77***
			(0.26)	(0.21)	(0.22)
Quarterly return on assets	niq_at	Quality	0.65***	0.25*	0.41*
			(0.23)	(0.15)	(0.24)
Quarterly return on equity	niq_be	Profitability	0.30	0.38**	0.34
			(0.24)	(0.17)	(0.24)
R&D capital-to-book assets	rd5_at	Low Leverage	0.28	−0.00	0.12
			(0.33)	(0.24)	(0.39)
R&D-to-market	rd_me	Size	0.11	−0.14	−0.17
			(0.31)	(0.25)	(0.41)
R&D-to-sales	rd_sale	Low Leverage	0.15	−0.13	−0.42
			(0.31)	(0.24)	(0.37)
Residual momentum t-12 to t-1	resff3_12_1	Momentum	0.40	0.43**	0.28
			(0.28)	(0.20)	(0.29)
Residual momentum t-6 to t-1	resff3_6_1	Momentum	0.45*	0.64***	0.36
			(0.26)	(0.22)	(0.28)
Return on equity	ni_be	Profitability	0.78**	0.27	0.51*
			(0.30)	(0.17)	(0.26)
Return on net operating assets	ebit_bev	Profitability	0.80***	0.47**	0.82***
			(0.26)	(0.19)	(0.24)
Return volatility	rvol_21d	Low Risk	0.36	0.29	0.23
			(0.30)	(0.23)	(0.22)
Sales growth (1 quarter)	saleq_gr1	Investment	0.07	0.19	0.06
			(0.34)	(0.24)	(0.26)
Sales Growth (1 year)	sale_gr1	Investment	−0.07	0.32	0.17
			(0.31)	(0.23)	(0.31)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Sales Growth (3 years)	sale_gr3	Investment	−0.18	0.15	0.15
			(0.28)	(0.23)	(0.30)
Sales-to-market	sale_me	Value	−0.12	−0.15	−0.10
			(0.29)	(0.22)	(0.26)
Share turnover	turnover_126d	Low Risk	0.57*	0.35**	0.46
			(0.29)	(0.18)	(0.29)
Short-term reversal	ret_1_0	Short-Term Reversal	−0.36	0.15	0.15
			(0.36)	(0.21)	(0.25)
Standardized earnings surprise	niq_su	Profit Growth	−0.05	0.02	0.32
			(0.26)	(0.18)	(0.25)
Standardized Revenue surprise	saleq_su	Profit Growth	−0.07	−0.27	−0.02
			(0.26)	(0.18)	(0.22)
Tax expense surprise	tax_gr1a	Profit Growth	−0.22	−0.24	−0.30
			(0.24)	(0.19)	(0.22)
Taxable income-to-book income	pi_nix	Seasonality	0.41*	−0.12	0.08
			(0.25)	(0.15)	(0.25)
The high-low bid-ask spread	bidaskhl_21d	Low Leverage	−0.30	0.05	−0.25
			(0.30)	(0.21)	(0.21)
Total accruals	taccruals_at	Accruals	0.04	0.00	0.13
			(0.29)	(0.17)	(0.24)
Total skewness	rskew_21d	Short-Term Reversal	−0.06	−0.10	−0.14
			(0.27)	(0.17)	(0.18)
Year 1-lagged return, annual	seas_1_1an	Profit Growth	0.21	−0.07	−0.27
			(0.28)	(0.20)	(0.21)
Year 1-lagged return, nonannual	seas_1_1na	Momentum	0.19	0.32**	0.26
			(0.31)	(0.16)	(0.27)
Years 11-15 lagged returns, annual	seas_11_15an	Seasonality	−0.03	−0.18	−0.03
			(0.35)	(0.22)	(0.27)
Years 11-15 lagged returns, nonannual	seas_11_15na	Seasonality	0.02	−0.05	0.27
			(0.28)	(0.28)	(0.34)
Years 16-20 lagged returns, annual	seas_16_20an	Seasonality	0.05	0.10	−0.08
			(0.30)	(0.26)	(0.31)
Years 16-20 lagged returns, nonannual	seas_16_20na	Accruals	0.06	−0.28	0.22
			(0.30)	(0.28)	(0.39)
Years 2-5 lagged returns, annual	seas_2_5an	Seasonality	−0.30	−0.00	0.21
			(0.32)	(0.22)	(0.31)
Years 2-5 lagged returns, nonannual	seas_2_5na	Investment	−0.00	0.19	−0.04
			(0.30)	(0.21)	(0.28)

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Table A.1 – *continued from previous page*

Anomaly	JKP Variable	JKP Theme	Raw Complexity	Size → Complexity	IVOL → Complexity
Years 6-10 lagged returns, annual	seas_6_10an	Seasonality	−0.15	0.16	0.47**
			(0.28)	(0.19)	(0.23)
Years 6-10 lagged returns, nonannual	seas_6_10na	Low Risk	−0.11	−0.08	−0.06
			(0.29)	(0.19)	(0.25)

Notes: This table reports factor-level CAPM complexity-amplification alphas, defined as the CAPM alpha of the high-complexity anomaly return minus the low-complexity anomaly return, in percent per month. Raw Complexity denotes the independent complexity–characteristic sort without an additional conditioning characteristic. Size → Complexity and IVOL → Complexity condition first on size and idiosyncratic volatility, respectively, as described in the text. Newey–West HAC standard errors are reported in parentheses. The size-controlled specification excludes market equity, and the idiosyncratic-volatility-controlled specification excludes the 21-day Fama–French three-factor idiosyncratic-volatility characteristic. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

TABLE A.2: Factors With Largest Complexity-Amplification Alphas

Rank	Anomaly	CAPM Alpha
Panel A. Raw Complexity		
1	Quality minus Junk: Safety	0.97***
		(0.26)
2	Quality minus Junk: Composite	0.95***
		(0.28)
3	Idiosyncratic volatility from the CAPM (252 days)	0.82**
		(0.36)
4	Return on net operating assets	0.80***
		(0.26)
5	Return on equity	0.78**
		(0.30)
Panel B. Size → Complexity		
1	Change in long-term investments	0.66
		(0.43)
2	Residual momentum $t-6$ to $t-1$	0.64***
		(0.22)
3	Market beta	0.63***
		(0.22)
4	Quality minus Junk: Safety	0.56***
		(0.21)
5	Coefficient of variation for dollar trading volume	0.54***
		(0.18)
Panel C. IVOL → Complexity		
1	Frazzini–Pedersen market beta	0.90***
		(0.25)
2	Altman Z-score	0.82***
		(0.22)
3	Return on net operating assets	0.82***
		(0.24)
4	Quality minus Junk: Safety	0.77***
		(0.22)
5	Operating profits-to-book assets	0.73***
		(0.23)

Notes: This table reports the five largest CAPM complexity-amplification alphas within each specification, ranked separately by point estimate. Alphas are in percent per month. Raw Complexity denotes the independent complexity–characteristic sort without an additional conditioning characteristic. Newey–West HAC standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.