Equity Prices in a Granular Economy*

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Equity Prices in a Granular Economy

ABSTRACT

This paper explores the asset pricing implications of a granular economy, where a few firms are exceedingly large (the size of 'grains'). We present three new findings that support the idea that a more granular economy may be detrimental to investors, due to reduced diversification across stocks and heightened aggregate risk. First, the slope of the Security Market Line (SML) exhibits a negative relationship with the level of granularity. Second, the betting-against-beta (BAB) strategy performs well only during times of increased granularity, aligning with the SML's decreasing slope. Third, exposure to granularity is negatively priced, indicating that stocks performing well during increased granularity offer protection against diversification risk, thereby providing lower returns. These results underscore the critical role of granularity in understanding vital aspects of equity markets.

JEL Classification Numbers: G12, G14

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1. Introduction

Asset pricing models and examples discussed in investment finance classes generally assume firms to be atomistic, whereby idiosyncratic shocks get diversified away. However, a growing body of literature, initiated by Axtell (2001) and Gabaix (2011), indicates that the world is better characterized as a granular economy, where a few large firms play a significant role in the market. This is evident from examples like Apple and Microsoft, which accounted for over 13% of the market capitalization of the S&P500 in March 2023.[1] When some firms act more like grains (or even rocks), rather than atoms, idiosyncratic shocks can have substantial impact on aggregate market fluctuations. Neglecting the implications of such firm size distribution could lead to various anomalies in individual stock returns, as nontrivial effects of firm-specific risk on equity prices arise endogenously in a granular economy. It is therefore crucial to comprehend the implications of granularity for financial markets, particularly given the current dominance of some very large firms in the U.S. equity space.

This paper explores the asset pricing implications of a granular economy and uncovers three new findings. First, we show that the slope of the Security Market Line (SML) decreases when the economy becomes more granular, i.e. when the largest firm represents a greater share of the economy. Specifically, in times when granularity is reduced, portfolio betas are strongly and positively related to average equity returns, but the relation turns negative when granularity increases, thereby explaining the relatively 'flat' SML observed unconditionally. Second, the performance of the betting-against-beta (BAB) strategy appears to be particularly high when granularity increases, which is effectively when the slope of the SML decreases, but low otherwise. Third, we show that the exposure to granularity is priced negatively, such that stocks that perform well when granularity increases protect investors against a drop in diversification risk and are thus viewed as relatively safe assets.

Our work is founded on the fundamental premise that an increase in granularity, where larger firms dominate the market even more, has negative implications for investors. This is

[1] In addition, the five largest firms dominating the tech sector in the U.S. (Amazon, Apple, Facebook, Netflix, and Microsoft) have recently represented more than a fifth of the total stock market capitalization of the S&P500, providing a clear illustration of a granular equity market.

because individual shocks affecting these very large firms do not fully dissipate at the aggregate level, leading to their idiosyncratic risk becoming a significant factor in overall market risk. For example, consider the (hypothetical) unexpected death of Apple's CEO. While initially an idiosyncratic event, it can have far-reaching consequences on the entire market due to Apple's substantial weight in the market index. Such idiosyncratic shocks then transform into systematic risks rather than being effectively diversified away. The consequence of increased granularity is that it makes investors worse off by reducing potential diversification across stocks and heightening market risk.

Following this insight, our empirical analysis shows that granularity plays a pivotal role in understanding key aspects of asset pricing, especially regarding the properties of the conditional CAPM. We find that the slope of the SML is negatively related to the level of granularity in the U.S. equity market. We consider straightforward measures of granularity, such as the market capitalization of the 20, 50, or 100 largest firms relative to that of the entire market, or the excess Herfindahl-Hirschman Index (HHI) proposed by Gabaix and Koijen (2022). Our main finding is summarized in Figure 1. We plot the average returns of various test portfolios against their conditional market betas, conditioning on the monthly change in granularity. The slope of the SML is positive in months of decreasing granularity (Panel A) and negative in months of increasing granularity (Panel B). We show with Fama-MacBeth regressions that the slope of the SML is statistically different across both subsamples. We obtain similar findings with alternative test assets, namely 20 equally-weighted and value-weighted beta portfolios, 48 industry portfolios, or 25 size and book-to-market portfolios. Overall, the negative relation between the conditional slope of the SML and granularity is statistically significant and robust to the choice of portfolios and granularity measures.

We verify that these results are not capturing alternative explanations suggested by the existing literature. First, we control for the market return to ensure that increased granularity is not simply capturing times of negative market returns. Second, we control for investor sentiment, as Antoniou, Doukas, and Subrahmanyam (2015) show that the slope of the SML is positive during pessimistic sentiment periods and negative during optimistic periods. Third, we control for inflation as money illusion, intensified by high inflation rates, can also affect the

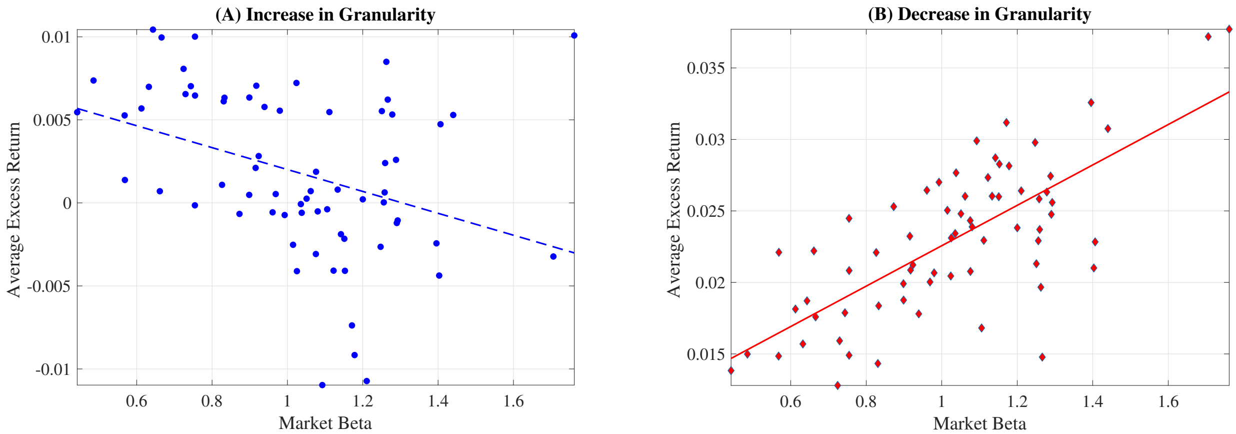

Figure 1. Conditional Security Market Line and Granularity. This figure shows the average conditional monthly returns against the previous month's average conditional market betas for 10 value-weighted and 10 equal-weighted beta portfolios, and 48 industry portfolios. We separate portfolio returns by months of increases ($\Delta G_t > 0$ in Panel A) and decreases ($\Delta G_t < 0$ in Panel B) in granularity, where granularity, G_t, is the market value of largest 20 firms in the market as fraction of total market capitalization. We report the regression fit as a measure of the Security Market Line. Data is monthly and from CRSP. The sample spans the period 1973-2020.

slope of the SML (Cohen, Polk, and Vuolteenaho, 2005). We also account for the impact of funding liquidity conditions on the slope of the SML using the TED spread, following Frazzini and Pedersen (2014). In all cases, the negative relation between the slope of the SML and our measures of granularity remains significant and economically meaningful.

Building on the finding that the relation between the SML slope and granularity is negative, we can revisit one of the most studied implications of the 'too-flat' SML: the betting-against-beta (BAB) strategy. Frazzini and Pedersen (2014) show that a long position in low-beta assets and a short position in high-beta assets produce significantly positive risk-adjusted returns. Our analysis predicts that such returns should be particularly high when granularity increases (i.e., when the slope of the SML decreases), while they should be reduced when granularity decreases. We provide strong evidence for this prediction and find that BAB returns are significantly and positively related to changes in granularity, even after controlling for alternative predictors. This analysis sheds new light on the conditional performance of the BAB strategy.

Lastly, we examine the role of granularity for the cross-sectional pricing of individual stocks and equity portfolios. An increase in granularity means that the large firms become even greater players in the market, such that their idiosyncratic shocks do not completely wash out at the aggregate level. Higher granularity is thus detrimental for investors as it translates into lower diversification and thus higher aggregate risk. Investors should then demand extra compensation to hold stocks with negative granularity exposure and they are willing to pay high prices for stocks with positive granularity exposure. Confirming this prediction, we find that portfolios that are long in stocks with the lowest granularity beta and short in stocks with the highest granularity beta yield an annualized risk-adjusted return of about 4.23%. This result is robust to controlling for a battery of risk factors and stock characteristics that are known to explain the cross-section of stock returns. That is, the exposure to granularity changes is strongly and negatively priced among U.S. stocks.

This paper builds on the literature analyzing the SML and the speculative demand for high-beta stocks. Stocks with lower systematic exposure tend to have a larger CAPM alpha, a phenomenon first documented by Black (1972) and referred to as the 'low-risk effect'. Several studies reconcile this observation with shorting and leverage constraints. When borrowing is constrained, investors willing to invest more during favorable conditions increase their exposure to systematic risk by tilting their portfolios toward high-beta assets.[2] These assets tend to underperform and involve lower alphas. This is precisely what we find when granularity decreases, which corresponds to better economic conditions for investors. Frazzini and Pedersen (2014) formalize this mechanism by constructing a model with constrained investors who bid up high beta assets to address their limited leverage to invest in rewarding opportunities. The authors further document a significant return on a strategy that shorts high beta and holds low beta assets, i.e., the BAB strategy. Our contribution is to show that the return of the BAB strategy is concentrated in times of granularity increases, i.e., when the slope of the SML weakens.

Alternatively, Bali, Brown, Murray, and Tang (2017) show that the buying pressure exerted towards high beta stocks arises from lottery preferences of investors, while Liu, Stambaugh, and Yuan (2018) argue that this phenomenon only appears among over-priced stocks. Antoniou et al. (2015) associate this effect to investor sentiment: In optimistic periods, bullish trades

[2]Jylhä (2018) finds that exogenous changes in the margin requirement corroborate the pricing implications of the constrained leverage story.

distort prices, while prices are in line with the CAPM in pessimistic periods. The low-risk effect can also be attributed to aggregate disagreement among investors, which affects speculative demand for financial assets (Hong and Sraer, 2016). Additional explanations include money illusion among investors (Cohen et al., 2005), arbitrage (Huang, Lou, and Polk, 2016), the sensitivity of asset prices to macroeconomic announcements (Savor and Wilson, 2014), or the informational gap between investors and the econometrician (Andrei, Cujean, and Wilson, 2023). We contribute to this literature by revisiting the conditional slope of the SML through the lens of a granular economy, providing novel insights into the fundamental relationship between a firm's equity risk premium and systematic risk.

The idea of studying a granular economy is not new. As firm size in the economy is not normally but power-law distributed, the law of large numbers does not apply and firm-specific risk of relatively large firms (grains) becomes incompressible (Gabaix, 2011; Gabaix and Koijen, 2022). Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) find that systematic versus firm-specific risk are not easily distinguished, suggesting that the two are fundamentally linked and driven by a common component. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) explore the channels through which firm size distribution determines how firm-specific shocks propagate and affect firm volatilities.[3] Building on this literature, we show that granularity in the U.S. stock market plays a fundamental role in driving the conditional CAPM and provide a new angle to understand the cross-section in stock returns. Overall, the contribution of this paper is to shed light on the asset pricing implications of granularity in the equity market.

2. Hypothesis Development

In this section, we present several key hypotheses to guide our empirical investigation into the impact of granularity on asset prices. Building upon the works of Axtell (2001) and Gabaix (2011), among others, we consider an economy to be granular when a small number of very large

[3]Granularity also implies that country size and trade affect macroeconomic volatility (di Giovanni and Levchenko, 2012), that large firms drive business cycles (Carvalho and Grassi, 2019), and that firm-specific shocks propagate through production networks and affect firms' sales growth and stock prices (Barrot and Sauvagnat, 2016).

firms ('grains') significantly contribute to overall fluctuations. We argue that this characterization equally applies to the U.S. equity market, where a handful of prominent companies hold substantial market weight. For instance, in March 2023, Apple and Microsoft alone accounted for over 13% of the S&P500's market capitalization, compared to a mere 0.4% if all firms were of equal size.

A key implication of granularity in the equity market is that any individual shocks to the very large firms do not completely wash out at the aggregate level, such that their idiosyncratic risk become a substantial component of market risk. As an example, consider the news of a major fine on Microsoft. Although this news may be purely idiosyncratic, it will affect the market as a whole given the large weight of Microsoft's stock in the market index. Such idiosyncratic shocks thereby become systematic in nature instead of being diversified away. An increase in granularity, whereby the large firms become even more sizable in terms of their share of the market, is thus detrimental for investors as it leads to reduced diversification and increased market risk. Additionally, Herskovic et al. (2020) suggest a strong link between firm size dispersion and equity volatility's factor structure, another important source of aggregate risk.

Following this discussion, one can expect granularity to play a pivotal role in comprehending crucial aspects of financial markets. Yet, little is currently known about the specific impact of granularity on asset pricing. Consequently, we put forth three main hypotheses that we will empirically examine in this study.

First, fluctuations in granularity should be informative about the slope of the Security Market Line (SML). The intuition follows from the evidence that investors and mutual funds often face constraints on shorting (Almazan, Brown, Carlson, and Chapman, 2004) and leverage (Frazzini and Pedersen, 2014), such that they prefer trading high-beta stocks, as demonstrated by Hong and Sraer (2016) and Barber and Odean (2000), among others. So, when granularity decreases, which corresponds to more favorable market conditions for investors, high-beta stocks become an attractive option for them to capitalize on their market outlook. As a result, the value of high-beta stocks should increase relative to low-beta stocks. In contrast, an increase in granularity, being perceived unfavorably by investors, should prompt them to sell high-beta stocks while purchasing low-beta stocks. The selling pressure exerted on high-beta stocks would imply a negative price response for these stocks, relative to the low-beta ones. This mechanism has direct implications for the conditional Capital Asset Pricing Model (CAPM), giving rise to the following hypothesis:

Hypothesis 1: *Changes in granularity are linked to the slope of the Security Market Line (SML). Specifically, the SML exhibits a steeper slope during periods when granularity decreases than when it increases.*

Second, building upon our first hypothesis, which posits a negative relationship between the slope of the SML and granularity, we can extend our analysis to explore the impact of granularity on the performance of the betting-against-beta (BAB) strategy. Frazzini and Pedersen (2014) demonstrate that a long position in low-beta assets combined with a short position in high-beta assets generates significant positive risk-adjusted returns. Such returns are expected to be notably high during times of increasing granularity (when the SML slope decreases) and diminished during times of decreasing granularity. Therefore, we propose:

Hypothesis 2: *The performance of the betting-against-beta (BAB) strategy is influenced by changes in granularity: the BAB strategy should yield positive returns in periods of increasing granularity and negative returns in periods of decreasing granularity.*

Finally, we anticipate that fluctuations in granularity play a crucial role in determining the cross-sectional pricing of individual stocks and equity portfolios, as higher granularity corresponds to reduced diversification and increased aggregate risk. Stocks that perform well when granularity increases protect investors against such diversification risk and are viewed as relatively safe assets. Investors are willing to pay higher prices for these stocks and accept lower returns. In contrast, stocks that perform badly when granularity increases are riskier assets, such that investors would demand extra compensation in the form of higher expected return to hold stocks with negative granularity exposure. Therefore, stocks that are more exposed to changes in granularity should deliver lower expected excess returns. Our last testable hypothesis is then:

Hypothesis 3: *The exposure to granularity changes is negatively priced: Investors should demand additional compensation to hold stocks with negative granularity exposure, and they should be willing to pay higher prices for stocks exhibiting positive granularity exposure.*

3. Empirical Analysis

This section presents and discusses the main empirical results of the paper regarding the implications of granularity on asset prices. We test the three hypotheses developed in Section 2. We first provide details on the data we employ in our empirical study and then describe the main methodology.

3.1. Data and key variables

We obtain stock and Treasury bond return data, spanning January 1973 to December 2020, from the Center for Research in Security Prices (CRSP).[4] We use the value-weighted index of all listed shares (NYSE, Amex, and Nasdaq) as our stock market proxy.

3.1.1. Test assets

Our analysis will largely focus on stock portfolios, although we will also consider firm-level observations for robustness. To obtain returns on beta-sorted portfolios, we first estimate (pre-formation) betas for each individual stock using 60 months of monthly returns and sort stocks into 20 portfolios according to their beta. We then compute returns on value-weighted and equal-weighted portfolios. We also retrieve returns on alternative test assets (e.g., 25 size and book-to-market, 48-industry portfolios) from Kenneth French's website.

[4]CRSP starts including firms traded on NYSE American and NASDAQ in 1962 and 1972, respectively. The latter almost doubles the number of firms in the CRSP universe. We consider data from 1973 to avoid having our analysis contaminated by substantial changes in the number of firms.

3.1.2. Granularity measures

We consider various measures of granularity in the equity market. Our approach builds on Gabaix (2011), who defines granularity in the economy as the sum of sales of the top 20 firms as a fraction of the GDP. We adapt this measure to the U.S. equity market and measure granularity, denoted by G_t, as the market capitalization value of the top 20 firms as a fraction of the total market capitalization from CRSP. We alternatively consider the market capitalization value of the top 50 and top 100 firms as fraction of total market capitalization. In addition, we compute a measure of market concentration using the excess Herfindahl-Hirschman Index (HHI) proposed by Gabaix and Koijen (2022). These measures are defined in Table A.1.

Figure 2 plots various measures of granularity over the 1973-2020 period, which strongly varies over time. A higher value of an index means that the U.S. equity market is more granular, i.e. the economy is dominated by a few large firms. For example, the market weight of the top 20 firms represents 21% of the total market, on average, and ranges between 16% and 30%. Panel A in Table A.2 presents the descriptive statistics for all measures of granularity.

FIGURE 2 ABOUT HERE

There is a high degree of comovement across the different measures, as reported in Panel A of Table A.3.[5] We can thus conclude that alternative granularity measures capture similar information. We hereafter focus the analysis on the top 20 firms, for convenience. Finally, Table I reports the name and equity market weight of the largest five firms in the USA, at the end of every year. Noteworthy, the top firms, such as Apple or Microsoft (Technology), Citigroup (Banking), Exxon Mobil (Energy), Walmart (Retail), and Pfizer (Pharmaceutical), typically cover a wide range of industries.

Our prior that an increase in granularity corresponds to unfavorable conditions for investors, by reducing potential diversification across stocks and heightening market risk. Consistent with this view, Table II shows that higher granularity is associated with negative market reactions,

[5] Panel B of Table A.3 shows correlation coefficients between granularity and various variables that are known to predict the slope of the SML. Granularity appears to be weakly correlated with investor sentiment (0.03), inflation (-0.12), market returns (-0.27), and the TED spread (0.27), whose roles are discussed in Section 3.2.3.

lower GDP growth, a fall in consumer confidence, as well as higher economic and financial uncertainty.

TABLES I AND II ABOUT HERE

3.2. Granularity and the slope of the SML

To test whether the slope of the SML decreases with granularity, we provide three types of analysis. First, we separate times of increases and decreases in granularity and plot the conditional SML in each case. Second, we conduct a Fama-MacBeth estimation and test the difference in the SML slope across both subsamples. Third, we use a regression analysis to exploit the time-series of the SML slope and study how it varies with granularity after controlling for alternative explanations. We describe each of these approaches below and discuss the results, which validate our Hypothesis 1.

For each portfolio, we compute the conditional (post-formation) betas over rolling a 60-month-windows using monthly returns. Specifically, we estimate the CAPM beta $\beta_{p,t}$ of portfolio p in month t by estimating the regression

$$R_{p,\tau} - R_{f,\tau} = \alpha_{p,t} + \beta_{p,t}(R_{mkt,\tau} - R_{f,\tau}) + \epsilon_{p,\tau}, \tag{1}$$

where $R_{p,\tau}$ is the return on portfolio p at time $\tau \in \{t-59, t\}$, $R_{f,\tau}$ is the risk-free rate given by the 1-month Treasury bill return, and $R_{mkt,\tau}$ is the market return. This procedure yields a times series of conditional beta estimates for each portfolio, $\hat{\beta}_{p,t}$.

3.2.1. Subsample analysis

As a first exercise, we compute the average conditional betas for every test asset, $\hat{\beta}_p^H$ and $\hat{\beta}_p^L$, where the superscript H and L denote the months when granularity increases ($\Delta G_t > 0$) and decreases ($\Delta G_t < 0$), respectively. We then compute the corresponding average conditional portfolio returns over the following month, R_p^H and R_p^L. Figure 3 plots the average realized excess returns R_p^H against $\hat{\beta}_p^H$ and R_p^L against $\hat{\beta}_p^L$ for the 20 value-weighted portfolios in Panel A and the 48 industry portfolios in Panel B. The slope of the SML is negative in times of increasing granularity and positive in times of decreasing granularity. Figure 4 shows that the results are robust to using alternative granularity measures. Consistent with our theoretical prediction, the slope of the SML is thus negatively related to changes in granularity.

FIGURES 3 AND 4 ABOUT HERE

3.2.2. Fama-MacBeth

We then present results using the classic two-step testing procedure for the CAPM. For the second-stage regressions, we adopt the Fama-MacBeth procedure and compute coefficients separately by estimating, for each month t, the following cross-sectional regressions:

$$R_{p,t}^H - R_{f,t}^H = a^H + \gamma^H \hat{\beta}_{p,t-1}^H + \epsilon_p^H \tag{2}$$

and

$$R_{p,t}^L - R_{f,t}^L = a^L + \gamma^L \hat{\beta}_{p,t-1}^L + \epsilon_p^L, \tag{3}$$

where H (L) denotes months with increases (decreases) in granularity, i.e., $\Delta G_t > 0$ ($\Delta G_t < 0$). We calculate the sample coefficient estimates, $\bar{\gamma}^H$ and $\bar{\gamma}^L$, as the average across time of the cross-sectional estimates, while their standard error equal the time series standard deviation of the cross-sectional estimates divided by the square root of the respective sample lengths. We can thus test whether the difference in coefficient estimates is statistically significant by applying a simple t-test for a difference in means.

Table III reports the average of the conditional slope of the SML, estimated with Equations (2) and (3), and the difference of the two, with the t-statistics reported in parentheses. Panel A reports the results for different test assets. Column 1 uses 20 equally-weighted beta portfolios (our benchmark case), Column 2 uses 20 value-weighted beta portfolios, Column 3 uses 48 industry portfolios, Column 4 uses 25 size and book-to-market portfolios, while Column 5 uses a mix of 10 equally-weighted, 10 value-weighted beta, 10 industry, and 6 size and book-to-market portfolios. We find that the slope of the SML is always positive when the U.S. market becomes less granular (i.e., the largest firms playing a smaller role in terms of market capitalization), while the slope of the SML turns negative in times of higher granularity. A test for the difference, based on the t-test comparing means between months of increase vs. decrease in granularity, indicates that the slope of the SML is statistically different across both subsamples.

Panel B reports the conditional slope of the SML using different measures of granularity. The difference in the conditional means is always significantly different from zero and with the expected sign. Hence, the negative relation between the conditional slope of the SML and granularity is statistically significant and robust to the choice of test assets and granularity measures.

TABLE III ABOUT HERE

3.2.3. Controlling for alternative explanations

As the last exercise, we estimate the conditional slope of the SML and study its relation with granularity controlling for alternative explanations. Specifically, we first estimate, for every month t, the slope of the SML with a cross-sectional regression of portfolio excess returns on their beta obtained in the previous month:

$$R_{p,t} - R_{f,t} = a_{0,t} + \gamma_t \hat{\beta}_{p,t-1} + \epsilon_{p,t} \tag{4}$$

and then regress the estimates of the slope of the SML, denoted by $\hat{\gamma}_t$, on changes in granularity ΔG_t, controlling for existing predictors. Panel A of Table IV reports the results, using t-statistics based on Newey-West standard errors with an optimal number of lags. Column 1 presents the univariate results. In Columns 2 through 5, we increment the specification by including various control variables. All variables are standardized to facilitate the interpretation of their coefficients.

TABLE IV ABOUT HERE

First of all, the univariate results indicate that the slope of the SML decreases with granularity, computed as the market capitalization of the top 20 firms as a fraction of the total market capitalization in the U.S. The regression coefficient equals -0.285 with a t-statistic of -4.20, which is both statistically and economically significant. A one-standard-deviation increase in granularity implies a decrease in the slope of the SML by almost one third (0.285) of a standard deviation in the slope.

We verify that the role of granularity is not subsumed by alternative mechanisms, as suggested by the existing literature. First, we control for market (excess) returns to ensure that increased granularity is not simply capturing times of negative market returns. In addition, Savor and Wilson (2014) find that the slope of the SML is particularly strong when macroeconomic news is scheduled for announcement, which corroborate with large market return days. Column 2 of Table IV shows that the effect of granularity decreases by almost one half but remains highly statistically significant. Hence, we can safely rule out the possibility that variations in granularity are merely capturing return fluctuations of the market. Note that we do not need to separate days with and without macroeconomic announcements, following Savor and Wilson (2014), given our analysis is monthly.

Alternatively, Antoniou et al. (2015) show that the slope of the SML is positive during pessimistic sentiment periods and negative during optimistic periods. Optimism attract equity investment by less sophisticated traders in risky opportunities (high beta stocks), while such traders stay along the sidelines during pessimistic periods (see, e.g., Grinblatt and Keloharju (2001); Lamont and Thaler (2003)). Thus, high beta stocks become overpriced in optimistic periods, which induces the negative slope of the SML. Following Antoniou et al. (2015), we use the Baker and Wurgler (2006)'s index of investor sentiment, which we obtain from the authors' website. Column 3 of Table IV suggests that granularity does not reflect changes in sentiment, as the coefficient of interest remains similar and significant.

Another explanation for the time-variation in the SML slope is money illusion. Modigliani and Cohn (1979) argue that inflation, by driving a wedge between nominal versus real discount rates, brings about major errors in how investors price equity. Based on the same argument, Cohen et al. (2005) hypothesize that money illusion, intensified by high inflation rates, affects the slope of the SML. They show that the slope of the SML preceded by low inflation months is steeper than the slope of the SML preceded by high inflation months. Following Cohen et al. (2005), we control for lagged inflation using monthly changes in the producer price index, but the impact of granularity remains unchanged, as indicated by Column 4 of Table IV.

Finally, we account for changes in funding liquidity conditions. Frazzini and Pedersen (2014) use the TED spread as a measure for funding conditions and show that it is negatively correlated with contemporaneous returns on the betting-against-beta (BAB) strategy. We include the TED spread in our set of control variables to account for the potential impact of funding conditions on the slope of the SML. This control has no effect on the role of granularity, as evidenced by Column 5 of Table IV.

Overall, the negative relation between the slope of the SML and granularity remains significant after controlling for existing explanations such as aggregate market fluctuations, money illusion, investor sentiment, and funding liquidity conditions. In addition, the results are robust to using the SML slope estimated with the cross-section of individual stocks (Panel B of Table IV) instead of portfolios.

3.3. Revisiting Betting Against Beta

In this section, we revisit one of the most studied implications of the 'too-flat' slope of the SML, which is known as the betting-against-beta (BAB) strategy. Frazzini and Pedersen (2014) show that a long position in low-beta assets and a short position in high-beta assets produces significant positive risk-adjusted returns. Our Hypothesis 2 predicts that such returns should be particularly high when granularity increases, while they should be reduced when granularity decreases. We now test this prediction and shed new light on the conditional performance of the BAB strategy.

3.3.1. Conditional Beta-sorted Portfolio Alpha

We start by studying the conditional performance of 10 beta-sorted portfolios with respect to granularity. Consistent with the rest of the paper, we first use the (pre-formation) betas estimated for each individual stock using 60 months of monthly returns. We then sort stocks into 10 portfolios according to their beta and compute the equally-weighted returns for each portfolio. Following prior work, we exclude stocks with prices below $5 to ensure that results are not driven by small, illiquid stocks.

The unconditional CAPM alpha of each portfolio is the intercept of a regression of the portfolio's excess return on the market excess return over the whole sample. For the conditional analysis, we first split the portfolio returns into two subsamples corresponding to months when granularity decreases ($\Delta G_t < 0$) and increases ($\Delta G_t > 0$). Then, we estimate the intercept of the regression based on each subsample.

Figure 5 illustrates the annualized CAPM alphas of each portfolio in the unconditional case (Panel A), when granularity increases (Panel B), and when granularity decreases (Panel C). The results reproduce the typical betting-against-beta pattern in the unconditional estimation: the low-beta portfolios exhibit positive alphas, while the high-beta portfolios exhibit negative alphas. However, the strength of the relation varies according to granularity: we find a more (less) negative relation between CAPM alphas and the corresponding betas in Panel B (Panel C), which is when granularity increases (decreases). Note that alphas are on average negative in Panel B, which indicates that relatively-small stocks underperform the market when granularity increases, i.e., when the larger firms become even larger and thus outperform the market. The opposite applies to Panel C.

FIGURE 5 ABOUT HERE

We present the results of the 10 beta-sorted portfolios and assess their statistical significance in Table V. The first two rows report the post formation market betas and time series averages of monthly excess returns for each of the portfolios. We then report the unconditional (Panel A) and the conditional (Panel B) portfolio alphas. The rightmost column presents the difference in estimates between the top beta and the bottom beta portfolios, i.e., P_{10}-P_1. In Panel C, we conduct a robustness analysis when we orthogonalize changes in granularity to excess market returns, thus avoiding that our conditioning analysis merely reflects times of good vs. bad market conditions. The conditional results reported in Panels B and C of Table V are qualitatively similar. In both cases, we find that the high-beta portfolio (P10) alpha is statistically lower than the low-beta portfolio (P1) alpha when granularity increases, but the relation becomes statistically insignificant (and of the opposite sign) when granularity decreases. That is, the classic BAB pattern appears to be concentrated in times of increasing granularity.

TABLE V ABOUT HERE

3.3.2. Explaining BAB Returns with Granularity

In this section we examine the conditional performance of the long-short BAB strategy, which we construct as buying the low-beta portfolio (P_1) and selling the high-beta portfolio (P_{10}). That is, the long portfolio is an equal-weighted average of the bottom decile stocks, when stocks are ranked according to their beta, whereas the short portfolio is an equal-weighted average of the top decile stocks.

We first compute the conditional average return of the BAB strategy. The first two rows in Table VI show the average BAB return for months when granularity increases ($\Delta G_t > 0$) and decreases ($\Delta G_t < 0$), respectively. We use four different granularity measures corresponding to each of the columns and report, in each case, the average BAB return (with t-statistics in parentheses). The granularity measures are based on the market value of the 20, 50, and 100 largest firms as fraction of total market capitalization, as well as the excess Herfindahl-Hirschman Index (exHHI). The last row reports the difference between the conditional averages and the corresponding t-statistics. In all cases, the BAB strategy yields a positive average return when granularity increases and a negative average return when granularity decreases. Hence, the performance of the BAB strategy appears to be indeed highly related to granularity.

TABLE VI ABOUT HERE

For robustness, we then examine how the return on this BAB strategy relates to changes in granularity by estimating the following regression:

$$r_{BAB,t} = b + \beta_G \Delta G_t + \mathbf{X}_t' \beta_C + \epsilon_t, \tag{5}$$

where the BAB return $r_{BAB,t}$ is regressed on granularity changes ΔG_t, while $\mathbf{X}_t$ is a vector of financial conditions that we use as control variables. The set of controls includes excess market returns, lagged inflation, lagged BAB returns, and the TED spread. Table A.4 presents the results, which indicate that BAB returns are significantly and positively related to changes in granularity, even after controlling for alternative predictors. The effect is statistically significant and of the expected sign.

In sum, we provide evidence that the performance of the BAB strategy is particularly high when granularity in the U.S. stock market increases, which is when the slope of the SML decreases, as predicted by our theory.

3.4. Cross-Sectional Pricing

We now examine the role of granularity for the cross-sectional pricing of individual stocks and equity portfolios. Specifically, we estimate stock exposure to our granularity index and provide the out-of-sample performance of ex-ante measures of the granularity beta in predicting the cross-sectional variation in future stock returns. We start with a portfolio-level analysis and then present univariate and multivariate cross-sectional regression results.

Following Hypothesis 3, our conjecture is that the exposure to granularity changes is negatively priced. As granularity increases, the large firms become even larger players of the market, such that their idiosyncratic shocks do not completely wash out at the aggregate level. Higher granularity is thus detrimental for investors as it translates into lower diversification. Stocks that perform well when granularity increases protect investors against such diversification risk and are viewed as relatively safe assets. Investors are willing to pay higher prices for these stocks and accept lower returns. In contrast, stocks that perform badly when granularity increases are riskier assets, such that investors would demand extra compensation in the form of higher expected return to hold stocks with negative granularity exposure. Therefore, stocks that are more exposed to changes in granularity should deliver higher expected excess returns.

3.4.1. Portfolio Sorts

We first test this prediction using a portfolio sorting approach. The portfolio sorting procedure has the attractive interpretation of representing implementable trading strategies.

A firm's granularity exposure is obtained from monthly rolling regressions of its excess stock returns on the contemporaneous changes in the granularity index using a 60-month fixed window estimation:

$$R_{i,\tau} - R_{F,\tau} = a_{i,t} + \beta_{i,t}^{\Delta G} \Delta G_\tau + \beta_{i,t}^{MKT} (R_{MKT,\tau} - R_{F,\tau}) + \epsilon_{i,\tau}, \tag{6}$$

where $R_{i,\tau}$ is the return on stock i at time $\tau \in \{t-59, t\}$, $R_{F,\tau}$ is the risk-free rate given by the 1-month Treasury bill return, ΔG_τ is the monthly change in our baseline granularity measure, and $R_{MKT,\tau}$ is the CRSP market return. Controlling for market returns exclusively ensures that the estimation process for pre-formation granularity betas is least noisy (see Ang, Hodrick, Xing, and Zhang, 2006). We nevertheless control, in our post-formation analysis, for various risk factors typically used in the cross section of equity returns

Table VII presents the main portfolio results. For each month, we form decile portfolios by sorting individual stocks based on their granularity betas ($\beta^{\Delta G}$), where decile 1 contains stocks with the lowest $\beta^{\Delta G}$ during the past month, and decile 10 contains stocks with the highest $\beta^{\Delta G}$. We use the granularity beta estimated in month $t-2$ to ensure that the sorting process is based solely on past information. The first two columns in Table VII report the average ex ante and ex post granularity betas for the decile portfolios formed on $\beta^{\Delta G}$. The next 3 columns present the average excess returns and the alphas on the equal-weighted portfolios, while the last 3 columns report the results using the value-weighted portfolios.

TABLE VII ABOUT HERE

We observe significant cross-sectional variation in the average values of $\beta^{\Delta G}$, ranging between -6.2 to 2.8. The average return difference between decile 10 (high-$\beta^{\Delta G}$) and decile 1 (low-$\beta^{\Delta G}$) is -0.41% per month with a Newey and West (1987) t-statistic of -2.98. This result indicates that stocks in the lowest granularity beta decile generate about 4.96% more annual returns compared to stocks in the highest granularity beta decile. We can see that the return difference arises from both the outperformance by low-$\beta^{\Delta G}$ stocks and the underperformance by high-$\beta^{\Delta G}$ stocks, given that the returns of decile 1 is significantly positive while that of decile 10 is significantly negative. We thus uncover a significant negative granularity premium.

This finding is robust to the consideration of different factor models, which allow to compute risk-adjusted returns (alphas). Following Bali, Brown, and Tang (2017), we first compute α_4, which is the intercept from the regression of the excess portfolio returns on a constant, excess market return, a size factor, an investment factor, and a profitability factor. We also compute α_7, which is relative to market, size, book-to-market, investment, profitability, liquidity, and momentum factors. In both cases, the return difference between the high-$\beta^{\Delta G}$ and low-$\beta^{\Delta G}$ stocks remains negative and statistically significant. The results strengthen, both economically and statistically, using value-weighted portfolios: the negative granularity premium based on α_7, for example, increases (in absolute value) from -0.35% per month to -0.94%, while the t-stat increases from -2.93 to -4.73. So these results are clearly not driven by small and potentially illiquid stocks.

Overall, this portfolio-level analysis indicates that buying stocks with the lowest granularity beta and shorting stocks with the highest granularity beta yield an annualized risk-adjusted return of about 4.23%. Notably, this granularity premium is driven by both the outperformance by stocks with negative granularity beta and the underperformance by stocks with positive granularity beta. Consistent with our theoretical prediction that higher granularity translates into higher aggregate risk, these results indicate that investors demand extra compensation to hold stocks with negative granularity exposure and that they are willing to pay high prices for stocks with positive granularity exposure.

3.4.2. Cross-Sectional Regressions

We now examine the cross-sectional relation between the uncertainty beta and expected returns at the stock level using Fama and MacBeth (1973) regressions. For consistency, we use the granularity betas estimated from specification (6). We then compute the time-series averages of the slope coefficients from the regressions of one-month-ahead stock returns on the granularity beta ($\beta^{\Delta G}$) with different sets of control variables. Table VIII reports the results with the Newey-West t-statistics in parentheses.

TABLE VIII ABOUT HERE

The univariate regression results reported in the first column indicate a negative and statistically significant relation between the granularity beta and the cross-section of future stock returns. This result is economically meaningful, as based on Table VII, the interdecile range in beta is about 9 ($\cong$ 2.82+6.16), so that a stock that switches from the first to the tenth decile has an expected excess return that decreases by $0.073 \times 9 = 0.66\%$ per month.

We then gradually add controls in the remaining columns and find that the results continue to be robust. Column 2 adds the exposure to the market (Fama and French, 1992). In Column 3, we account for the exposure to the economic and financial uncertainty indices of Jurado, Ludvigson, and Ng (2015), following Bali et al. (2017). In Column 4, we add the idiosyncratic volatility (IVOL) of Ang et al. (2006) and the maximum daily return of stocks within every month (MAX), used in Bali, Cakici, and Whitelaw (2011). In Column 5, we include the coskewness measure (COSKEW) of Harvey and Siddique (2000) and the firm-level illiquidity measure (ILLIQ) of Amihud (2002). In Column 6, we control for short-term reversal (REV) of Jegadeesh (1990) and the momentum measure (MOM) of Jegadeesh and Titman (2001). The slope of the granularity beta remains negative and highly significant after controlling for these risk factors and stock characteristics. The results are robust across different measures of granularity, as reported in Table A.5. In addition, Table A.6 shows that the granularity beta has long-term predictive power, as the average slopes on $\beta^{\Delta G}$ continue to be negative and significant when predicting 1-month to 12-month-ahead returns. The predictability uncovered with this analysis can therefore be reasonably exploited by investors.

We can conclude that the exposure to granularity is priced negatively in stocks, consistent with the view that an increase in granularity is viewed negatively by investors because it translates into lower aggregate diversification. Stocks that perform badly when the market becomes more granular are then viewed as riskier and command a higher risk premium.

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Table I
Top 5 Firms by Market Capitalization, 1975-2020

This table reports the name and equity market weight of the largest five firms in the USA, as observed at the end of calendar year. These firms include Amazon (AMZN), Apple (AAPL), AT&T, Citigroup (CITI), Coca Cola (KO), Eastman Kodak (EK), Exxon (XON), Exxon Mobil (XOM), Facebook (FB), General Electrics (GE), General Motors (GM), Google (GOOG), Johnson & Johnson (JNJ), IBM, Intel (INTC), Microsoft (MSFT), Phillip Morris (MO), Procter & Gamble (PG), Schlumberger (SLB), and Walmart (WMT). The last column reports the total market value of the tope five firms as a fraction of total market capitalization. All weights are reported in percentages. Equity data is from CRSP. The sample spans 1975 to 2020.

	Firm #1		Firm #2		Firm #3		Firm #4		Firm #5		
Year	Name	Weight	Name	Weight	Name	Weight	Name	Weight	Name	Weight	Total Weight
1975	IBM	4.12	AT&T	4.09	XON	2.46	EK	1.76	GM	1.66	14.11
1980	IBM	3.36	AT&T	2.96	XON	2.24	GM	1.35	SLB	1.05	10.96
1985	IBM	4.30	XOM	1.93	GE	1.49	GM	1.35	AT&T	1.08	10.15
1990	XOM	1.90	IBM	1.84	GE	1.81	AT&T	1.35	MO	1.13	8.03
1995	GE	1.69	AT&T	1.50	XOM	1.49	KO	1.30	WMT	1.01	6.99
2000	MSFT	2.98	GE	2.58	CSCO	2.11	INTC	1.95	XOM	1.70	11.32
2005	GE	2.31	XOM	2.02	MSFT	1.73	CITI	1.54	WMT	1.34	8.94
2010	XOM	1.92	MSFT	1.56	WMT	1.28	PG	1.13	AAPL	1.10	6.99
2015	AAPL	2.36	XOM	1.28	MSFT	1.15	JNJ	0.95	WMT	0.83	6.57
2020	AAPL	3.17	MSFT	3.04	AMZN	2.34	GOOG	1.01	FB	0.76	10.32

Table II
Variation in Granularity versus Economic & Financial Indicators

This table reports the coefficient of a regression where changes in granularity are regressed on a constant and a financial or economic indicator: monthly excess market returns (MKT), changes in GDP, consumer confidence (Conf), economic (Econ_{unc}) and financial (Fin_{unc}) uncertainty, the volatility of excess market returns (σ_{MKT}) or the VIX index. Economic data are retrieved from the website of Federal Reserve Bank of St. Louis. The daily returns (with distribution) of the CRSP value-weighted index are used to get monthly excess returns (MKT) by (i) compounding the daily returns within each calendar month into a monthly return and (ii) subtracting the risk-free rate, as obtained from Kenneth French's website. The standard deviation of the daily returns within a month is annualized to yield σ_{MKT} for that month. The old VIX methodology (now the VXO), which starts in Jan. 1986, is prepended to the VIX series, which was backdated only to Jan. 1990. Newey-West t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1979 to December 2020.

	MKT	ΔGDP	ΔConf	$\Delta\text{Econ}_{\text{unc}}$	$\Delta\text{Fin}_{\text{unc}}$	$\Delta\sigma^2_{\text{MKT}}$	ΔVIX
	-0.259^{***}	-0.152^{***}	-0.124^{**}	0.172^{***}	0.196^{***}	0.219^{***}	0.248^{***}
	(-4.79)	(-4.35)	(-2.45)	(3.05)	(4.33)	(4.27)	(4.51)
Adj. R^2 (%)	6.73	2.21	1.59	2.96	3.85	4.84	6.97
Obs.	576	192	515	576	576	575	419

Table III
Conditional SML Slope from Fama-MacBeth Regressions

This table reports the estimated conditional slope of the security market line (SML) based on Fama-MacBeth regressions. Every month, excess portfolio returns are regressed on post-formation market betas of the same portfolios from the previous month. Each panel reports the time-series average of the SML slope estimated for months when granularity increases ($\hat{\gamma}^H$) and when it decreases ($\hat{\gamma}^L$). The difference between the two is reported in the last row. t-statistics (in parentheses) are calculated using the standard deviation of the time series of the coefficient estimates. In Panel A, the slope of the SML is estimated across five different test assets: 20 equally-weighted (Column 1) and 20 value-weighted (Column 2) beta portfolios, 48 industry portfolios (Column 3), 25 size and book-to-market portfolios (Column 4), and a portfolio composed of 10 value-weighted, 10 equally-weighted beta portfolios, 10 industry portfolios, and 6 size and book-to-market portfolios (Column 5). Panel B reports results for different granularity measures when the test asset is the 20 equally-weighted beta portfolio. Granularity is the market value of the largest 20 (Column 1), 50 (Column 2), and 100 (Column 3) firms as fraction of total market capitalization, Herfindahl-Hirschman index (Column 4), and the excess excess Herfindahl-Hirschman index (exHHI) of Gabaix and Koijen (2022) (Column 5). Beta portfolios are formed based on monthly individual stock returns. All other portfolio returns are from Kenneth French's data library. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Equity data is from CRSP. The sample spans January 1973 to December 2020.

Panel A: Conditional mean of SML slope across test assets					
	(1) 20EW	(2) 20VW	(3) 48 Ind.	(4) 25 S. & BM	(5) 36 Assets
$\hat{\gamma}^H$	-0.142***	−0.065	−0.116***	−0.255***	−0.110**
	(-2.99)	(−1.23)	(−2.73)	(−4.20)	(−2.25)
$\hat{\gamma}^L$	0.252***	0.294***	0.140***	0.158***	0.237***
	(5.13)	(5.83)	(3.17)	(2.89)	(4.92)
$\hat{\gamma}^H - \hat{\gamma}^L$	-0.394***	−0.359***	−0.256***	−0.413***	−0.347***
	(-5.77)	(−4.91)	(−4.18)	(−5.05)	(−5.06)

Panel B: Conditional mean of SML slope across granularity measures					
	(1) Top20	(2) Top50	(3) Top100	(4) HHI	(5) exHHI
$\hat{\gamma}^H$	-0.142***	−0.196***	−0.223***	−0.128***	−0.128***
	(-3.03)	(−4.31)	(−4.89)	(−2.77)	(−2.77)
$\hat{\gamma}^L$	0.252***	0.335***	0.359***	0.250***	0.250***
	(5.20)	(6.71)	(7.23)	(5.07)	(5.07)
$\hat{\gamma}^H - \hat{\gamma}^L$	-0.394***	−0.532***	−0.583***	−0.378***	−0.378***
	(-5.85)	(−7.87)	(−8.63)	(−5.60)	(−5.60)

Table IV
Slope of the SML and Granularity

This table reports coefficients from a regression where the slope of the SML is regressed on a constant, changes in granularity (ΔG_t), and various control variables. The slope of the SML is obtained from regressing equally-weighted monthly returns of 20 beta portfolios (Panel A) or individual stock returns on same stocks (Panel B) on the previous month's market betas of the same assets. Conditional betas are estimated by rolling a 60-month window. Granularity (G_t) is the market value of the 20 largest firms in the market as fraction of total market capitalization. Control variables include excess market re turns ($R_{m,t}$-$R_{f,t}$), investor sentiment (Sentiment_t), lagged inflation (Inflation_{t-1}), and the TED spread (TED_t). Details about the variables are provided in Table A.1. All variables are standardized. Newey-West *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

Panel A: Portfolio Level

	(1)	(2)	(3)	(4)	(5)
ΔG_t	−0.285***	−0.127***	−0.129***	−0.127***	−0.161***
	(−4.20)	(−2.82)	(−2.96)	(−2.91)	(−3.06)
$R_{m,t}$-$R_{f,t}$		0.751***	0.743***	0.744***	0.759***
		(15.14)	(15.37)	(15.44)	(15.96)
Sentiment_t			−0.115***	−0.108***	−0.113**
			(−3.35)	(−3.18)	(−2.29)
Inflation_{t-1}				0.031	0.005
				(1.21)	(0.19)
TED_t					0.149***
					(3.92)
Adj. R^2(%)	7.90	61.95	63.18	63.19	63.95
Observations	455	455	455	455	409

Panel B: Individual Stock Level

	(1)	(2)	(3)	(4)	(5)
ΔG_t	−0.277***	−0.127**	−0.130**	−0.129**	−0.150**
	(−3.85)	(−2.20)	(−2.34)	(−2.31)	(−2.28)
$R_{m,t}$-$R_{f,t}$		0.712***	0.703***	0.703***	0.732***
		(12.15)	(12.37)	(12.39)	(12.69)
Sentiment_t			−0.142***	−0.138***	−0.132**
			(−3.69)	(−3.54)	(−2.49)
Inflation_{t-1}				0.016	−0.000
				(0.62)	(−0.02)
TED_t					0.102***
					(2.89)
Adj. R^2(%)	7.64	57.42	59.39	59.32	409
Observations	455	455	455	455	409

Table V
Beta-sorted Portfolio Returns and Granularity

This table reports beta-sorted portfolio returns by granularity. The first two rows report the market beta and the time series average of 10 equally-weighted beta-sorted portfolios (Columns P1 to P10). The rightmost column corresponds to the difference between the high-beta portfolio and the low-beta portfolio (P10-P1). CAPM alpha is the intercept from a regression where excess portfolio returns are regressed on excess market returns. Panel A presents the unconditional results. Panel B presents results conditional on increases ($\Delta G_t > 0$) and decreases ($\Delta G_t < 0$) in granularity, measured as the value of the 20 largest firms as fraction of total market capitalization. Panel C conditions the analysis on ΔG_{orth}, which is given by ΔG orthogonalized to excess market returns. Newey-West t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRPS. The sample spans January 1973 to December 2020.

PTF	P1 (Low β)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High β)	P10-P1
Panel A: Unconditional											
Beta	0.568	0.661	0.754	0.872	0.960	1.037	1.142	1.247	1.395	1.705	1.137
Ex. Ret	1.124	1.093	1.157	1.169	1.228	1.285	1.267	1.278	1.422	1.599	0.475
CAPMα	0.327	0.166	0.099	−0.055	−0.119	−0.171	−0.334	−0.471	−0.535	−0.792	−1.119
	(2.33)	(1.19)	(0.75)	(−0.41)	(−0.93)	(−1.35)	(−2.77)	(−3.87)	(−3.96)	(−4.13)	(−4.53)
Panel B: Conditional on ΔG											
CAPMα, $\Delta G > 0$	-0.358**	−0.568***	−0.719***	−0.916***	−1.055***	−1.181***	−1.371***	−1.638***	−1.786***	−2.220***	−1.862***
	(-2.06)	(−3.36)	(−4.53)	(−5.95)	(−6.76)	(−7.98)	(−8.90)	(−11.48)	(−10.65)	(−9.70)	(−6.49)
CAPMα, $\Delta G < 0$	1.101***	0.968***	0.927***	0.835***	0.831***	0.819***	0.659***	0.639***	0.640***	0.479*	−0.622*
	(6.28)	(5.22)	(5.06)	(4.63)	(4.62)	(4.63)	(3.84)	(3.72)	(3.29)	(1.65)	(−1.65)
Panel C: Conditional on ΔG_{orth}											
CAPMα, $\Delta G_{orth} > 0$	-0.490**	−0.715***	−0.825***	−1.085***	−1.225***	−1.347***	−1.518***	−1.788***	−1.872***	−2.247***	−1.757***
	(-2.62)	(−3.87)	(−4.88)	(−6.70)	(−7.63)	(−8.69)	(−9.80)	(−11.99)	(−10.69)	(−9.47)	(−5.56)
CAPMα, $\Delta G_{orth} < 0$	1.103***	0.922***	0.882***	0.822***	0.820***	0.819***	0.659***	0.631***	0.578***	0.399	−0.628*
	(6.48)	(5.63)	(5.41)	(5.40)	(5.42)	(5.46)	(4.54)	(4.47)	(3.33)	(1.42)	(−1.74)

Table VI
Conditional BAB Returns by Granularity Changes

This table reports the conditional mean of betting-against-beta (BAB) returns by changes in granularity. We construct BAB returns from the strategy that holds the low-beta stocks and sells the high-beta stocks. The long portfolio is an equally-weighted average of the bottom decile stocks, when stocks are ranked according to their beta, whereas the short portfolio is an equally-weighted average of the top decile stocks. The conditioning criteria correspond to changes in four measures of granularity $\mathrm{G_t}$: the market value of the largest 20, 50, and 100 firms as fraction of total market capitalization, as well as the excess Herfindahl-Hirschman Index (exHHI). The first two rows show the average BAB return for months when granularity increases ($\Delta\mathrm{G_t} > 0$) and decreases ($\Delta\mathrm{G_t} < 0$), respectively. The last row reports the difference between the conditional means and the test of the difference. Newey-West *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

	ΔTop20	ΔTop50	ΔTop100	ΔexHHI
$\mathrm{r_{BAB,\Delta G>0}}$	0.014***	0.019***	0.021***	0.014***
	(3.60)	(5.16)	(5.71)	(3.45)
$\mathrm{r_{BAB,\Delta G<0}}$	-0.023***	-0.030***	-0.031***	-0.023***
	(-5.79)	(-7.68)	(-8.05)	(-5.89)
(1)-(2)	0.037***	0.049***	0.052***	0.037***
	(6.63)	(9.11)	(9.77)	(6.59)

Table VII
Cross-sectional Pricing with Portfolios

This table reports the properties of ten granularity portfolios. Each month stocks are sorted into deciles based on their exposure to granularity where the first (tenth) decile contains stocks with lowest (highest) granularity betas. Granularity is the market value of the largest 20 firms as fraction of total market capitalization. $\beta^{\text{pre}}_{\Delta G}$ is the average of preformation granularity betas of individual stocks, $\beta^{\text{post}}_{\Delta G}$ is the port-formation granularity beta, and Ex-Ret is the average excess return on individual stocks in each decile. The estimated constant of a regression where portfolio returns are regressed on a set of equity risk factors is denoted by α: α_4 is relative to market, size, investment, and profitability factors, while α_7 is relative to market, size, book-to-market, investment, profitability, liquidity, and momentum factors. Newey-West t-statistics are reported in parentheses.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

		Equal weighted				Value Weighted			
Decile	$\beta^{\text{pre}}_{\Delta G}$	$\beta^{\text{post}}_{\Delta G}$	Ex-Ret	α_4	α_7	$\beta^{\text{post}}_{\Delta G}$	Ex-Ret	α_4	α_7
Low	−6.15	−2.87	1.709***	0.868***	0.852***	−2.67	2.502***	1.586***	1.504***
			(5.37)	(9.42)	(10.31)		(7.22)	(10.34)	(10.51)
2	−3.35	−2.59	1.435***	0.542***	0.644***	−2.26	1.977***	1.034***	1.115***
			(5.30)	(6.26)	(9.17)		(6.99)	(9.23)	(9.80)
3	−2.40	−2.29	1.302***	0.427***	0.442***	−1.73	1.778***	0.923***	0.879***
			(5.39)	(5.09)	(7.78)		(7.31)	(8.89)	(7.51)
4	−1.77	−2.24	1.240***	0.344***	0.402***	−1.75	1.653***	0.819***	0.761***
			(5.33)	(4.22)	(6.70)		(7.03)	(8.04)	(7.65)
5	−1.26	−2.07	1.228***	0.352***	0.401***	−1.47	1.627***	0.785***	0.695***
			(5.63)	(4.07)	(6.85)		(7.81)	(9.04)	(7.31)
6	−0.80	−2.01	1.161***	0.303***	0.383***	−1.22	1.439***	0.622***	0.465***
			(5.39)	(3.56)	(6.56)		(7.34)	(7.34)	(5.73)
7	−0.34	−1.87	1.101***	0.232***	0.263***	−1.18	1.209***	0.390***	0.345***
			(5.23)	(2.86)	(4.58)		(6.18)	(5.77)	(4.39)
8	0.16	−1.77	1.081***	0.217***	0.235***	−0.97	1.240***	0.422***	0.415***
			(5.41)	(3.01)	(5.22)		(7.06)	(7.66)	(6.27)
9	0.83	−1.72	1.070***	0.264***	0.267***	−0.58	1.160***	0.439***	0.317***
			(5.35)	(3.75)	(4.92)		(6.72)	(6.72)	(4.94)
High	2.82	−1.91	1.296***	0.559***	0.499***	−0.67	1.300***	0.766***	0.566***
			(5.21)	(5.76)	(5.83)		(6.29)	(6.80)	(5.10)
High-Low		0.97	−0.413***	−0.309**	−0.353***	2.00	−1.203***	−0.820***	−0.938***
			(−2.98)	(−2.32)	(−2.93)		(−4.98)	(−4.14)	(−4.73)

Table VIII
Cross-sectional Pricing with Fama-MacBeth Regressions

This table reports time-series averages of slope coefficients obtained from cross-sectional regressions where returns (%) on individual stocks in month t+1 are regressed on equity risk factor betas and firm characteristics from month t. The predictor of interest is the estimated granularity betas ($\beta^{\Delta G}$), where granularity is the value of the largest 20 firms in the market as fraction of total market capitalization. Controls include the market betas (β^{Mkt}), economic ($\beta^{Unc_{econ}}$) and financial ($\beta^{Unc_{fin}}$) uncertainty betas (Jurado et al., 2015), idiosyncratic volatility (IVOL), the max factor (MAX), co-skewness (COSKEW), illiquidity (ILLIQ), short-term reversal (REV), and momentum (MOM). Newey-West *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.177***	0.952***	0.857***	1.031***	1.200***	1.027***
	(5.35)	(5.77)	(5.18)	(6.02)	(6.53)	(5.70)
$\beta^{\Delta G}$	−0.073***	−0.086***	−0.088***	−0.090***	−0.100***	−0.052**
	(−3.97)	(−4.03)	(−4.11)	(−4.24)	(−4.17)	(−2.22)
β^{MKT}		0.199	0.252*	0.263**	0.202	−0.029
		(1.51)	(1.82)	(1.99)	(1.48)	(−0.22)
$\beta^{Econ,Unc}$			−0.009	−0.012	0.001	−0.012
			(−0.36)	(−0.48)	(0.03)	(−0.37)
$\beta^{Unc,Fin}$			−0.251***	−0.255***	−0.277***	−0.165***
			(−4.50)	(−4.57)	(−4.55)	(−2.67)
IVOL				−0.353	−0.589*	−0.371
				(−1.28)	(−1.91)	(−1.23)
MAX				−2.314***	−1.386	0.146
				(−3.18)	(−1.52)	(0.14)
COSKEW					−0.242*	−0.281**
					(−1.87)	(−2.21)
ILLIQ					−0.010***	−0.017***
					(−3.53)	(−4.51)
REV						−0.045***
						(−10.21)
MOM						0.567***
						(3.44)
Adj. R^2 (%)	0.43	2.65	3.14	3.44	3.90	5.67
Months	516	516	516	516	516	516
Firms	2947	2947	2947	2935	2375	1943

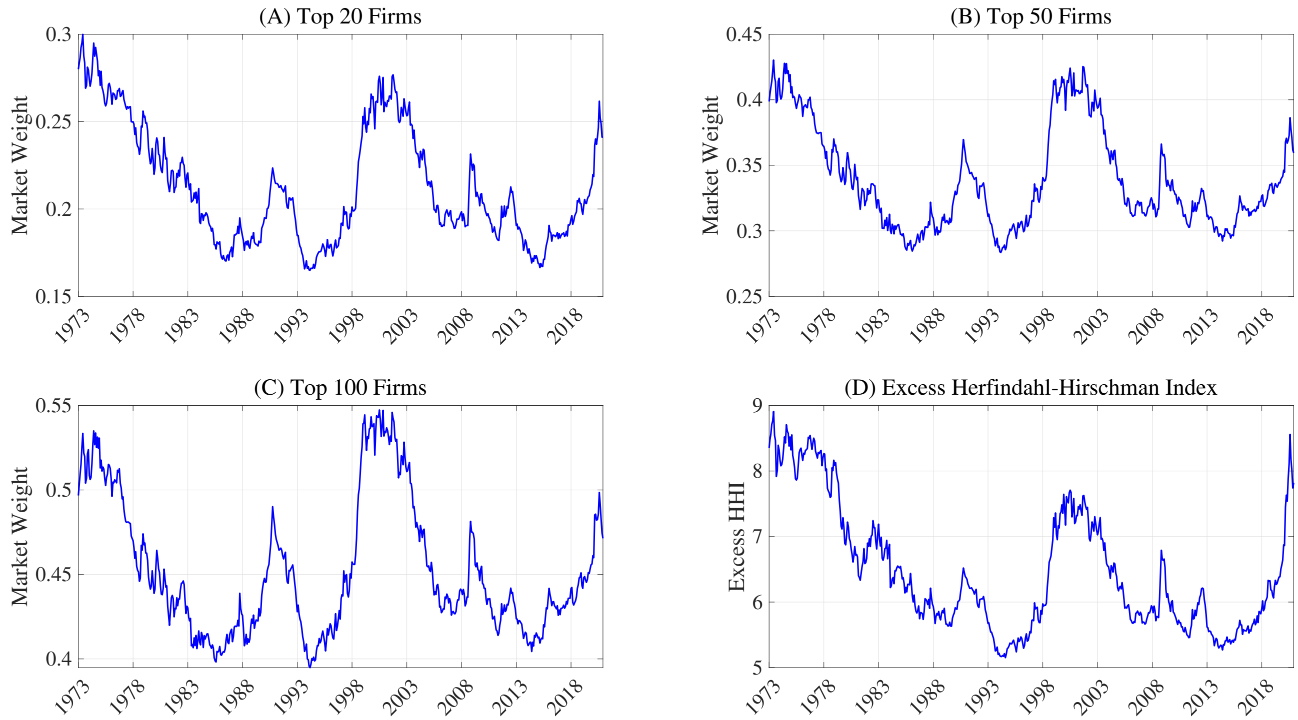

Figure 2. Time series of granularity. This figure shows the time series of four different measures of granularity. Panel A, B, and C, respectively, plot the market value of the largest 20, 50, and 100 firms in the market as fraction of total market capitalization. Panel D displays the excess Herfindahl-Hirschman Index, defined in Table A.1. Data is from CRSP. The sample spans January 1973 to December 2020.

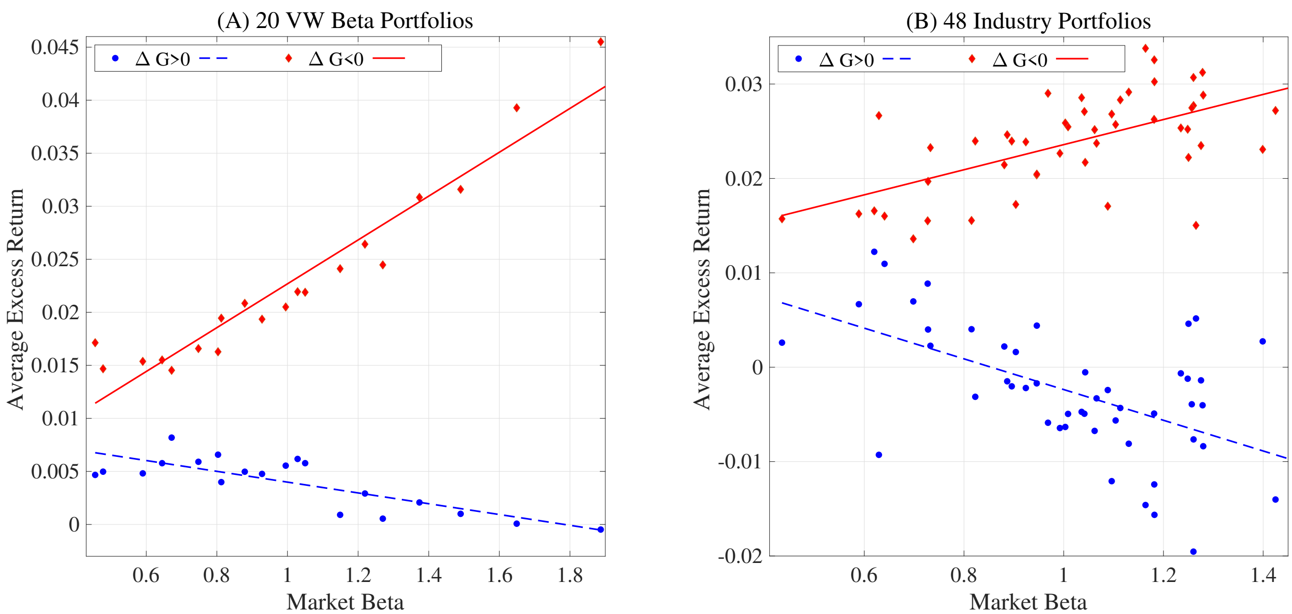

Figure 3. Conditional SML and granularity – Alternative portfolios. This figure shows the average conditional monthly returns against the average conditional market betas, computed in the previous month, of 20 value weighted beta portfolios (Panel A) and 48 industry portfolios (Panel B). We separate portfolio returns and corresponding betas for months when granularity increases ($\Delta G_t > 0$) versus when it decreases ($\Delta G_t < 0$). Granularity (G_t) is the market value of the largest 20 firms in the market as fraction of total market capitalization. Beta portfolios are formed based on monthly individual stock returns. Industry portfolio returns are from Kenneth French's data library. Individual equity data is from CRSP. The sample spans January 1973 to December 2020.

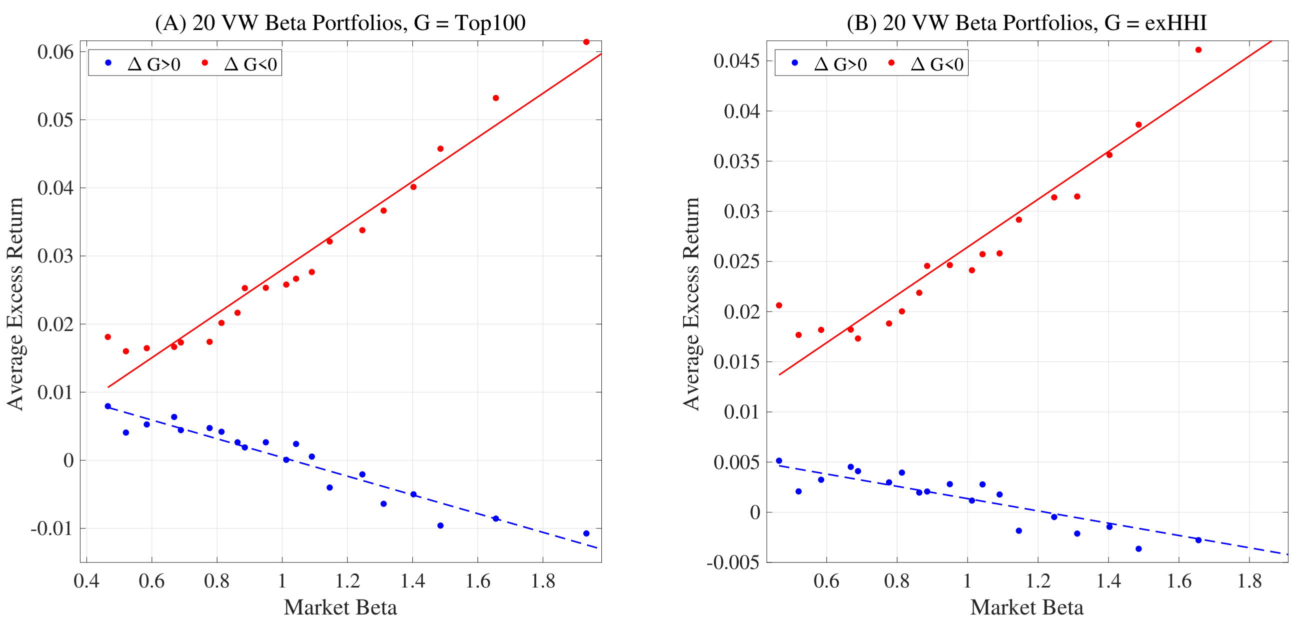

Figure 4. Conditional SML and granularity – Alternative granularity measures. This figure shows the average conditional monthly returns against the average conditional market betas, computed in the previous month, of 20 value weighted beta portfolios. We separate portfolio returns and corresponding betas for months when granularity increases ($\Delta \mathrm{G_t} > 0$) versus when it decreases ($\Delta \mathrm{G_t} < 0$). Granularity (G_t) is the market value of largest 100 firms in the market as fraction of total market capitalization in Panel A, and the excess Herfindahl-Hirschman Index in Panel B. Data is from CRSP. The sample spans January 1973 to December 2020.

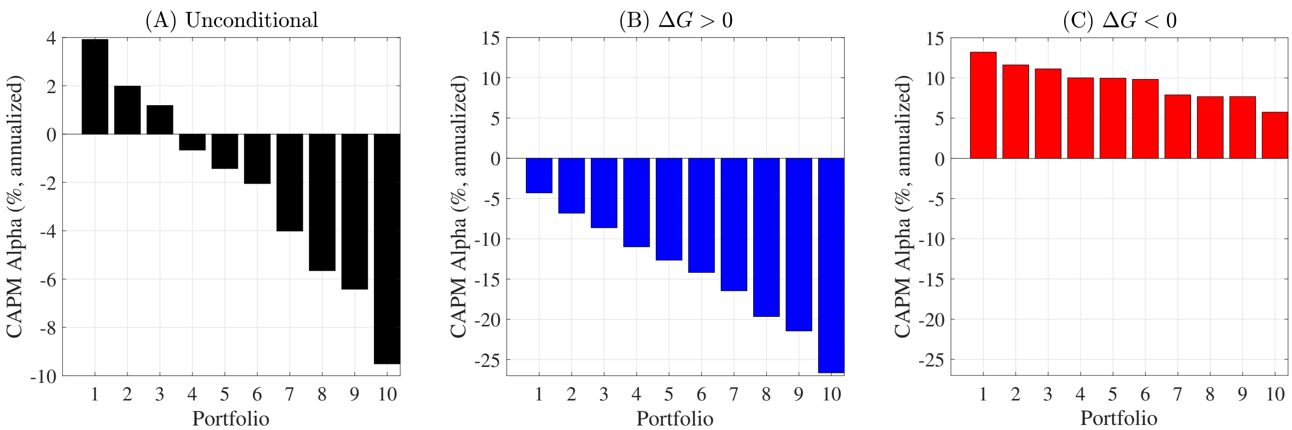

Figure 5. Conditional Alpha of Beta-sorted Portfolios. This figure plots the CAPM alphas of 10 equally-weighted portfolios based on beta-sorted stocks. The unconditional alpha of a portfolio is the intercept of a regression where portfolio excess returns are regressed on the market excess return and a constant over the whole sample. For the conditional analysis, we first split the portfolio returns into two subsamples corresponding to months when granularity decreases ($\Delta G_t < 0$) versus when it increases ($\Delta G_t > 0$). Granularity (G_t) is the market value of largest 20 firms in the market as fraction of total market capitalization. We then estimate the intercept of the regression for each subsample. Panel A displays the unconditional portfolio alphas, and Panels B and C report results for the conditional estimations. Beta portfolios are formed based on monthly individual stock returns. Data is from CRSP. The sample spans January 1973 to December 2020.

Online Appendix to

Equity Prices in a Granular Economy

(not for publication)

Abstract

This Online Appendix presents supplementary material and results not included in the main body of the paper.

Table A.1
Variation in Granularity versus Economic & Financial Indicators

This table defines the variables underpinning this study and the corresponding data sources. All series are retrieved monthly.

Variable	Definition	Source
G	Degree of granularity measured as the value of the largest firms in the U.S. as fraction of the total market capitalization of the CRSP universe. We use either the largest 20, 50, or 100 firms with the highest market capitalization. Alternatively, we consider the excess Herfindahl-Hirschman Index proposed by Gabaix and Koijen (2022), defined as exHHI = $\sqrt{-\frac{1}{N} + \sum_1^N w_i^2}$, or the Herfindahl-Hirschman Index (HHI = $\sum_1^N w_i^2$) where w_i the market value of firm i to total market capitalization, and N is the total number of firms.	Wharton Research Data Services
R_m - R_f	Market excess return, computed as the value-weighted return on the CRSP universe.	Wharton Research Data Services
Sentiment	Sentiment composite index based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.	Baker and Wurgler (2006)'s website
TED	The TED spread, measured by difference between the three-month Treasury bill and the three-month LIBOR rates based in US dollars.	Federal Reserve Bank of Saint Louis

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Table A.1 – *Continued from previous page*

Variable	Definition	Source
Inflation	Inflation measured as the exponentially weighted average (36-month window) of the log growth rates on the monthly Producer Price Index (PPI) for all commodities, following Cohen et al. (2005).	Federal Reserve Bank of Saint Louis
Size	Market capitalization of firms in millions of dollars.	Center for Research in Security Prices (CRSP)
REV	Short-term reversal is stock returns from prior month (Jegadeesh, 1990).	Center for Research in Security Prices (CRSP)
MOM	Momentum is cumulative return on stocks in the past 11 months (Jegadeesh and Titman, 2001).	Center for Research in Security Prices (CRSP)
COSKEW	Measure of co-skewness of Harvey and Siddique (2000), defined as $$COSKEW_{i,t} = \frac{\mathbb{E}\left[\epsilon_{i,t} R^2_{Mkt,t}\right]}{\sqrt{\mathbb{E}\left[\epsilon^2_{i,t}\right]}\,\mathbb{E}\left[R^2_{Mkt,t}\right]}, \quad \text{(A.1)}$$ where $\epsilon_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{Mkt,t})$ is the residual from regressing excess stock returns on the value weighted return on CRSP universe, obtained from a 60-month rolling window.	Center for Research in Security Prices (CRSP)

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Definition	Source
IVOL	Idiosyncratic volatility is defined as the standard deviation of $$\hat{\epsilon}_{i,t} = R_{i,t} - \big(\hat{\alpha}_i - \hat{\beta}^{MKT} R_{MKT,t} - \hat{\beta}^{SMB} R_{SMB,t} - \hat{\beta}^{HML} R_{HML,t}\big), \quad (A.2)$$ the residual from regressing daily excess stock returns on Fama and French three-factor model. We requite at lest 15 observations in each month to record IVOL (Ang et al., 2006).	Center for Research in Security Prices (CRSP)
ILLIQ	Amihud's illiquidity measure, defined as the absolute daily excess returns divided by corresponding trading volumes, averaged for each month Amihud (2002), $$\text{ILLIQ}_{i,t} = Avg\Big[\frac{\lvert R_{i,t}\rvert}{Vol_{i,t}}\Big]. \quad (A.3)$$	Center for Research in Security Prices (CRSP)
MAX	The maximum daily return of stocks within every month (Bali et al., 2011).	Center for Research in Security Prices (CRSP)
GDP	Gross Domestic Product.	Federal Reserve Bank of Saint Louis
Sent_{cons}	Consumer Sentiment: Surveys of Consumers of University of Michigan.	Federal Reserve Bank of Saint Louis
Econ_{unc}	Macroeconomic uncertainty measure of Jurado et al. (2015)	Author's website

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Table A.1 – *Continued from previous page*

Variable	Definition	Source
Fin_{unc}	Financial uncertainty measure of Jurado et al. (2015)	Author's website
σ^2_{MKT}	Market variance, computed at the variance of daily excess market returns in every month.	CRSP
VIX	CBOE volatility index. The VIX data is prepended to include VOX (the old VIX methodology) data, starting in January 1986.	CBOE website

Table A.2
Summary Statistics

This table reports the summary statistics of the main variables. Panel A considers different measures of granularity, including the market value of the largest 20, 50, and 100 firms in the market as fraction of total market capitalization, and the excess Herfindahl-Hirschman index (exHHI) of Gabaix and Koijen (2022). Panel B shows the estimated slope and intercept of the security market line (SML). Panel C presents the statistics for the control variables used in the regression analysis. The slope and intercept of the SML are estimated from Fama-MacBeth regressions based on 20 equally-weighted beta portfolios. Beta portfolios and granularity measures are based on individual stock information. Detailed description of the control variables is provided in Table A.1. Data is from CRSP. The sample spans January 1973 to December 2020.

Measure	Min	Max	Mean	Med	Std	1%	25%	75%	99%	Skw	Kur
Panel A: Granularity measures											
Top20	0.16	0.30	0.21	0.20	0.04	0.17	0.19	0.24	0.29	0.63	2.71
Top50	0.28	0.43	0.34	0.33	0.04	0.29	0.31	0.36	0.42	0.76	2.40
Top100	0.39	0.55	0.45	0.44	0.04	0.40	0.42	0.47	0.54	0.83	2.56
exHHI	0.05	0.09	0.06	0.06	0.01	0.05	0.06	0.07	0.08	1.12	3.86
Panel B: Slope and intercept of the SML (%)											
Slope	-20.2	33.6	0.49	0.33	6.22	-15.1	-2.89	3.45	17.6	68.1	612
Intercept	-20.3	11.3	0.67	1.02	3.81	-11.1	-0.88	2.73	8.94	-120	732
Panel C: Control variables (% - except Sentiment)											
R_m - R_f	-21.7	14.3	1.39	1.64	4.44	-11.1	-1.27	4.24	11.9	-0.51	4.78
Sentiment	-2.44	3.20	0.01	0.05	0.89	-2.25	-0.30	0.52	2.34	-0.29	4.18
Inflation	-0.39	0.99	0.13	0.13	0.21	-0.35	0.01	0.25	0.72	0.37	3.91
TED	0.12	3.15	0.56	0.45	0.44	0.13	0.25	0.69	2.27	2.10	9.41

Table A.3
Correlation between Variables

This table reports the cross correlation coefficients for the main variables used in this paper. Panel A shows the correlation between changes in different measures of granularity, including the market value of the largest 20, 50, and 100 firms in the market as fraction of total market capitalization, and the excess Herfindahl-Hirschman index (exHHI) of Gabaix and Koijen (2022). Panel B shows the correlation between changes in granularity (based on the top 20 firms), the excess market return (R_m - R_f), investor sentiment (Baker and Wurgler, 2006), inflation (Cohen et al., 2005), and the TED spread (Antoniou et al., 2015). Detailed description of the these variables is provided in Table A.1. Data is from CRSP. The sample spans January 1973 to December 2020.

Panel A: Change in granularity measures

Δ Measure	ΔTop20	ΔTop50	ΔTop100	ΔexHHI
ΔTop20	1	0.94	0.88	0.92
ΔTop50		1	0.97	0.87
ΔTop100			1	0.82
ΔexHHI				1

Panel B: Granularity and control variables

Variable	ΔG	R_m - R_f	Sentiment	Inflation	TED
ΔG	1	-0.23	0.05	-0.12	0.20
R_m - R_f		1	-0.10	0.06	-0.19
Sentiment			1	-0.08	0.06
Inflation				1	0.11
TED					1

Table A.4
BAB returns and Granularity

This table reports coefficients of a regression where betting-against-beta (BAB) returns are regressed on a constant, changes in granularity (ΔG_t), and various control variables. Granularity is the value of the largest 20 firms in the market as fraction of total market capitalization. We construct BAB returns from a strategy that holds low-beta, and sells high-beta stocks. The long portfolio is an equally-weighted average of the bottom decile stocks, when stocks are ranked according to their market beta, whereas the short portfolio is an equally-weighted average of the top decile stocks. Control variables include excess market return ($R_{m,t}$-$R_{f,t}$), lagged inflation ($\text{Inflation}_{t\text{-}1}$), lagged BAB returns ($r_{BAB,t\text{-}1}$), and the TED spread ($TED_t$). All variables are standardized. Newey-West *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

ΔG_t	0.346***	0.151***	0.150***	0.152***	0.196***	0.197***
	(5.67)	(3.45)	(3.41)	(3.54)	(3.44)	(3.51)
$R_{m,t}$-$R_{f,t}$		−0.723***	−0.724***	−0.714***	−0.738***	−0.738***
		(−14.26)	(−14.19)	(−14.40)	(−12.68)	(−12.70)
Sent_{t-1}			−0.009	0.008	0.028	0.028
			(−0.27)	(0.25)	(0.64)	(0.64)
Inflation_{t-1}				0.122***	0.153**	0.153**
				(3.74)	(2.49)	(2.53)
TED_t					−0.144***	−0.144***
					(−3.91)	(−3.90)
$r_{BAB,t-1}$						−0.001
						(−0.02)
Adj. R^2(%)	11.80	60.06	59.99	61.38	60.51	60.41
Observations	515	515	515	515	409	409

Table A.5
Cross-sectional Pricing with Alternative Granularity Measures

This table reports the time-series average of the slope coefficients obtained from monthly cross-sectional (Fama-MacBeth) regressions where returns in month t+1 are regressed on granularity betas from month t. Panel A reports univariate estimations, and Panel B shows multivariate estimations after controlling for market betas, economic and financial uncertainty betas, idiosyncratic volatility, the max factor, co-skewness, illiquidity, short-term reversal, and momentum. Each columns corresponds to different a measure of granularity, using the market value of the largest 50 and 100 firms as fraction of total market capitalization, as well as the Herfindahl-Hirschman Index (HHI) and its excess version (exHHI). Newey-West t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

Measure	Top_{50}	Top_{100}	exHHI	HHI
	Panel A: Univariate Regressions			
$\beta^{\Delta G}$	-0.085^{***}	-0.096^{***}	-1.520^{***}	-23.381^{***}
	(-3.61)	(-3.91)	(-3.17)	(-3.22)
Adj. R^2 (%)	0.53	0.54	0.41	0.41
Months	516	516	516	516
Firms	2925	2925	2925	2925
Controls	No	No	No	No
	Panel B: With Controls			
$\beta^{\Delta G}$	-0.058^{**}	-0.072^{**}	-1.227^{**}	-20.683^{**}
	(-2.03)	(-2.43)	(-2.17)	(-2.40)
Adj. R^2 (%)	5.70	5.69	5.59	5.58
Months	516	516	516	516
Firms	1943	1943	1943	1943
Controls	Yes	Yes	Yes	Yes

Table A.6
Predictive Power of Granularity Betas

This table reports the time-series average of slope coefficients obtained from monthly cross-sectional regressions where returns in month t+h are regressed on betas from month t. Panel A presents univariate estimations, and Panel B shows estimations after controlling for market betas, economic, and financial, uncertainty betas (Jurado et al., 2015), idiosyncratic volatility, the max factor, co-skewness, illiquidity, short-term reversal, and momentum. Newey-West t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Data is from CRSP. The sample spans January 1973 to December 2020.

Horizon	h=2	h=3	h=6	h=9	h=12
Panel A: Univariate Regressions					
$\beta^{\Delta G}$	-0.062^{***}	-0.060^{***}	-0.060^{***}	-0.059^{***}	-0.067^{***}
	(-3.44)	(-3.39)	(-3.52)	(-3.45)	(-4.15)
Adj. R^2 (%)	0.40	0.39	0.36	0.33	0.30
Months	515	514	511	508	505
Firms	2925	2897	2819	2744	2674
Controls	No	No	No	No	No
Panel B: With Controls					
$\beta^{\Delta G}$	-0.056^{**}	-0.045^{**}	-0.043^{*}	-0.039^{*}	-0.043^{**}
	(-2.44)	(-2.02)	(-1.90)	(-1.79)	(-2.07)
Adj. R^2 (%)	5.39	5.21	4.88	4.53	4.29
Months	515	514	511	508	505
Firms	1928	1913	1869	1829	1792
Controls	Yes	Yes	Yes	Yes	Yes