

Time-Varying U.S. Equity Market Integration

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Abstract

This paper proposes a new measure of market integration/segmentation for the U.S. equity market. In an integrated market, all assets earn the same risk premium for exposure to a given risk factor. We employ clustering methods to detect groups of assets that earn different factor risk premia and use the distance between these clusters as a measure of the degree of segmentation of the U.S. equity market. We find that the U.S. equity market segmentation varies significantly over time, from periods when unified factor risk prices cannot be rejected to periods with economically meaningful differences in factor risk compensation across latent groups. We propose a stylized “preferred habitat” model to understand the empirical findings. We find that market-wide trading activity, illiquidity, and recessions are associated with greater market segmentation, and decreased funding liquidity is associated with greater persistence in market segmentation.

Keywords: market efficiency, limits-to-arbitrage, liquidity, preferred habitat, clustering.

J.E.L. Classifications: G12, G14, C58.

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1 Introduction

In a fully integrated capital market, investors earn the same premium for bearing a given systematic risk no matter which asset delivers that exposure ([Sharpe, 1964](#); [Lintner, 1965](#); [Mossin, 1966](#); [Merton, 1973](#)). The principle of a single price of risk is built into the foundations of modern asset pricing, but frictions such as incomplete market participation, limits to arbitrage, funding constraints, slow-moving capital, and implementation costs can lead to violations of the law of one price ([Merton, 1987](#); [Shleifer and Vishny, 1997](#); [Brunnermeier and Pedersen, 2009](#); [Amihud, 2002](#); [Duffie, 2010](#); [Gromb and Vayanos, 2018](#); [Patton and Weller, 2022](#)). Whether these frictions are strong enough to segment the U.S. equity market is an empirical question and one, we argue, whose answer can change over time.

Rather than consider the static question of whether the U.S. equity market is perfectly integrated, we investigate the *dynamic* degree of integration vs. segmentation of this market. Are there periods when the market is fully integrated, and others when it is distinctly segmented? We use k -means clustering methods to identify groups of assets that earn different premia for the same factor exposure, without imposing in advance how many such groups exist or which assets belong to them. The distance between these groups, measured in earned risk premia, serves as our estimate of segmentation: the farther apart the clusters, the more segmented the market. We find that the market moves between periods when factor risk prices are statistically indistinguishable and periods of pronounced segmentation, with the latter concentrated in episodes of market stress.

We adopt a stylized “preferred habitat” model to understand the empirical results. In fixed-income markets, preferred-habitat models describe investors with demands for particular maturity segments and arbitrageurs who trade across those segments (e.g., see [Modigliani and Sutch, 1966](#) and [Vayanos and Vila, 2021](#)). We adapt this logic to equity portfolios. Investors may prefer particular regions of the equity cross section because of mandates, bench-

mark positions, institutional specialization, or trading clienteles (Barberis and Shleifer, 2003; Barberis et al., 2005; Kojen and Yogo, 2019). Arbitrageurs compress segmentation between these habitats, but only imperfectly when relative imbalances are large or cross-segment intermediation frictions bind.

Our empirical analysis of 234 equity portfolios over the period 1963-2024 delivers three main findings. First, factor risk price segmentation is statistically significant and strongly time-varying.¹ We estimate latent clusters of assets with different factor risk prices using the grouped-pricing estimator of Patton and Weller (2022), and strongly reject the null of market integration (i.e., equal risk prices across groups) in favor of market segmentation. We propose a new bootstrap test for a constant degree of market segmentation and we strongly reject in favor of time-varying market segmentation.

Next, we construct factor-specific segmentation indices from the cross-group dispersion in factor risk prices, as well as an aggregate segmentation index. We examine the indices at both the daily and monthly frequencies, the latter computed as the calendar-month average of the former, with the averaging helping to reduce measurement error.² To assess the economic relevance of segmentation, we compare portfolios constructed under common versus group-specific factor risk prices, and we find that in high-segmentation periods, the portfolio allowing for group-specific risk prices achieves a substantially higher Sharpe ratio than the portfolio imposing common risk prices. In low- and medium-segmentation periods, the gains are small and not significantly different from zero. Thus, the costs of assuming a common price of risk are concentrated precisely in periods when measured segmentation is high.

Third, we use a “preferred habitat” model to better understand the economic drivers of

¹Our baseline specification uses the Fama and French (2015)-Carhart (1997) six-factor model, described in detail in Section 2. We consider the three-factor model of Fama and French (1993) in Section 5 and find similar results.

²Note that time-varying measurement error can manifest as evidence of time-varying segmentation. Section 3.3 discusses how we measure variation in risk prices beyond that expected from time-varying measurement error.

time variation in market segmentation. The model implies that segmentation varies with relative factor-risk imbalances, intermediation-cost dispersion, and basis risk in the cross-habitat trade. Because these primitives are not directly observed, we use observable macro-financial state variables as proxies and estimate their relationship with our segmentation index via regression. We reject the joint null of no state dependence for each of the six factor-specific indices and for the aggregate index. We find that segmentation is most strongly tied to trading pressure and market liquidity. Aggregate trading volume and market-liquidity measures are the most robust state variables, while direct funding proxies, valuation, sentiment, and uncertainty play more selective roles. Viewed through the preferred-habitat framework, segmentation is widest when markets must absorb unusually large or costly relative factor-risk imbalances across latent groups. After correcting for measurement error, we also find that segmentation is highly persistent, and that this persistence itself varies with macro-financial states. For example, high trading volume is associated with greater segmentation, and also with faster mean reversion of the segmentation index.

The paper connects to various strands of the extant literature. First, it relates to work on international market segmentation and time-varying market integration. Classic contributions study how barriers to international investment, incomplete participation, and market liberalization affect whether assets are priced locally or globally (Stulz, 1981; Errunza and Losq, 1985; Bekaert and Harvey, 1995; de Jong and de Roon, 2005). A related literature develops empirical measures of the degree of integration, based on the explanatory power of global factors for country returns (Pukthuanthong and Roll, 2009) or on cross-country valuation differentials (Bekaert et al., 2011). Our focus is instead purely on the U.S. domestic equity market.³ Rather than explicit investment barriers, we study whether unobserved fric-

³Notably, Bekaert et al. (2011) treat the U.S. equity market as the benchmark for an integrated market. Measuring integration via the price of factor risk rather than via valuation ratios, we find that this benchmark market is itself segmented, to a time-varying extent.

tions impede unified pricing of factor risk exposures and we measure segmentation directly in risk prices rather than in return comovement or valuation ratios.

Second, our analysis naturally connects to studies of market frictions and arbitrage intermediation. Limits to arbitrage, liquidity frictions, funding constraints, preferred habitats, and intermediary balance-sheet constraints can prevent arbitrageurs from fully compressing price differences across assets or habitats (Shleifer and Vishny, 1997; Brunnermeier and Pedersen, 2009; Gârleanu and Pedersen, 2011; He and Krishnamurthy, 2013; Gârleanu et al., 2015; Gromb and Vayanos, 2018; Vayanos and Vila, 2021; Siriwardane et al., 2025). Our contribution is to measure segmentation directly in the price of factor risk and its variation over time. Instead of asking whether assets are locally or globally priced or whether a given characteristic earns a premium, we ask whether the same factor exposure commands the same compensation across latent clusters of the U.S. equity cross section, and how the distance between these clusters changes over time. In this respect, our segmentation index provides an empirical counterpart to models in which prices of risk in partially segmented markets become disconnected and are gradually realigned by slow-moving arbitrage capital (Duffie, 2010; Greenwood et al., 2018).

Finally, our paper connects to work on clustering methods in economics and finance. Bonhomme and Manresa (2015) provide econometric theory for identifying clusters from a panel of data, and for estimating a “time-varying fixed effect.” Evgeniou et al. (2023) use clustering methods to improve forecasts of stock returns by pooling across stocks that have similar characteristics. Closest to our work, Patton and Weller (2022) develop a clustering procedure to test whether a cross-section of assets contains distinct groups earning different factor risk premia. We adopt their inferential machinery but ask a different question: rather than testing only whether risk prices differ at a single point in time, we use the distance between the estimated clusters as a continuous measure of segmentation, track how it evolves,

and identify the economic states in which the market is most segmented.

The paper proceeds as follows. Section 2 describes the test assets, factor returns, and macro-financial state variables used in our empirical analysis. Section 3 constructs the market segmentation index, documents its time-series variation, and evaluates its economic relevance. Section 4 presents a preferred-habitat interpretation and analyzes the macro-financial states associated with the level and persistence of segmentation. Section 5 reports robustness analyses. Section 6 concludes. Additional details are presented in the Appendix, and further details are in a supplemental appendix.

2 Data

We measure segmentation in the U.S. equity market by estimating the magnitude of differences in risk premia earned by subsets of assets in the market. To implement such a method, we require a collection of test assets and a set of risk factors.

Our test assets are familiar value-weighted U.S. equity portfolios from Kenneth French’s data library. The portfolios are formed on market capitalization, book-to-market, medium-term momentum, short-term reversal, investment, operating profitability, and industries, providing a broad cross section of domestic equity portfolios. Although our approach can in principle be applied to individual securities, using portfolios leads to more precise estimates of factor exposures and avoids the entry, exit, and missing-return issues that arise in a daily panel of individual stocks. We use daily data over the period January 1963 to December 2024 and subtract the risk-free rate from each test-asset return to obtain excess returns. Because factor exposures are estimated using a trailing three-year window, the segmentation indices begin only once that estimation window is available. Analyses involving the macro-financial state variables begin in January 1986, reflecting the availability of the TED spread.

Table 1 reports the composition of the test-asset universe together with cross-sectional

Table 1: **Summary statistics for the test asset portfolios.** The table reports summary statistics on the daily value-weighted portfolio returns used in the empirical analysis. The sample period is January 1963 to December 2024. The columns titled “CS mean” and “CS st dev” report the cross-sectional mean and standard deviation across the portfolios within the portfolio family in the row.

<i>Portfolio</i>	N. portfolios	<i>Annualized average excess return</i>		<i>Annualized standard deviation</i>	
		CS mean	CS st dev	CS mean	CS st dev
Size	10	8.05	0.64	17.48	1.15
Book-to-market	10	8.16	1.44	17.47	1.60
Momentum	10	6.98	3.42	18.92	3.63
Short-term reversal	10	8.39	10.00	18.87	3.42
Investment	10	7.83	1.15	17.18	1.60
Operating profitability	10	6.99	1.42	17.58	1.70
Size-book-to-market	25	8.56	2.22	18.39	1.76
Size-momentum	25	8.53	3.60	18.97	3.01
Size-short-term reversal	25	8.10	13.39	18.89	2.87
Size-investment	25	8.74	1.91	17.90	1.69
Size-operating profitability	25	8.37	1.77	18.21	1.65
Industry	49	7.70	1.84	22.22	4.87
Total	234	8.11	5.15	19.12	3.42

summary statistics for the annualized average excess returns and annualized standard deviations of the underlying portfolios. The average annualized excess returns are relatively similar across most portfolio families, generally ranging from approximately 7% to 9%. Cross-sectional dispersion in average returns is much greater within the short-term-reversal portfolios, consistent with a wide spread across the underlying reversal sorts. The industry portfolios have the highest average annualized volatility, at 22.2%, and also exhibit the greatest cross-sectional dispersion in volatility.

For our factor model we augment the model of [Fama and French \(2015\)](#), which postulates five factors for the cross section of expected returns (MKT is the market return in excess of the risk-free rate, SMB is the size factor, HML is the value factor, RMW is the profitability

factor, and CMA is the investment factor), with the momentum factor of [Carhart \(1997\)](#) to obtain a six-factor model. In [Section 5](#) we employ the three-factor model of [Fama and French \(1993\)](#) and show that our main conclusions are robust to using this alternative specification. Returns on all factors are from Kenneth French’s data library.

In [Section 4](#) we investigate the relationship between our proposed measure of market segmentation and some well-known macro-financial variables. [Table 2](#) reports the sampling frequency and the transformation (to induce stationarity) used in the analysis. [Supplemental Appendix S.2](#) reports the data sources and construction details, including the TED-spread extension and the augmented VIX series. We stochastically de-trend aggregate trading volume by dividing it by a backward-looking two-year rolling average ([Campbell, 1991](#); [Gallant et al., 1992](#)). The Amihud measure is similarly normalized by its backward-looking two-year average, with higher values denoting greater illiquidity.

The daily segmentation index regressions use the date-level transformed variables, and state variables available only at the monthly frequency are forward-filled so that each day in a given month uses the transformed value available at the end of the prior month. For the monthly segmentation index regressions, continuous-valued daily variables are averaged within calendar months. Continuous variables are standardized separately for the daily and monthly regression samples, while indicator variables remain in zero-one units.

3 Time-varying segmentation in U.S. equities

This section constructs the empirical segmentation measure and documents its main properties. We first test whether the grouped-pricing framework uncovers significant departures from the benchmark of common factor risk prices. Next, we use cross-validation to select the number of latent clusters. We then construct estimation-error-adjusted factor-specific segmentation indices and their cross-factor aggregate at both daily and monthly frequencies.

Table 2: **Macro-financial state variables.** This table reports the observation frequencies and transformations used to induce stationarity for a collection of macro-financial variables.

<i>Variable</i>	<i>Frequency</i>	<i>Transformation</i>
TED spread	Daily	First difference
3-month Treasury bill rate	Daily	First difference
S&P 500 trading volume	Daily	Stochastic de-trend
JLN financial uncertainty	Monthly	First difference
Pastor-Stambaugh illiquidity	Monthly	Sign-flipped level
Amihud illiquidity	Daily	Stochastic de-trend
NBER recession indicator	Monthly	None
DJIA book-to-market ratio	Monthly	First difference
Three-year up-market indicator	Daily	None
VIX	Daily	Log first difference
Michigan consumer sentiment	Monthly	First difference
Baker-Wurgler sentiment	Monthly	First difference

Finally, we compare the mean-variance opportunity set implied by common and group-specific risk prices across periods with varying degrees of market segmentation.

3.1 Testing for market segmentation

Let $r_{i,t}^e$ denote the excess return on portfolio i on date t , and let $\beta_{i,t}$ denote its vector of factor exposures. The integrated-pricing benchmark imposes a common factor risk price,

$$r_{i,t}^e = \beta_{i,t}^\top \lambda_t + u_{i,t}. \quad (1)$$

In a segmented market the same risk exposures receive different compensation in different latent groups. If portfolio i belongs to group $\gamma_i \in \{1, \dots, G\}$, we write

$$r_{i,t}^e = \beta_{i,t}^\top \lambda_{0,t} + \beta_{i,t}^\top d_{\gamma_i,t} + u_{i,t}, \quad (2)$$

where $\lambda_{0,t}$ represents the “baseline” vector of risk prices and $d_{g,t}$ is the group- g deviation from that baseline. The group deviations are normalized to sum to zero across groups. Equation (2) collapses to (1) when all group deviations are zero, i.e., when the market is fully integrated. The grouped-pricing estimator of [Patton and Weller \(2022\)](#) is used to recover the factor risk prices across the different groups without requiring us to observe the underlying economic primitives. In Section 4.1 we propose a “preferred habitat” model to consider the sources of these deviations in terms of relative factor-risk imbalances, cross-group differences in intermediation costs, and basis risk.

To estimate the model in (2), we first construct portfolio-level factor exposures. For each portfolio i and date t , we estimate exposures using the previous three years of daily observations, ending before the return window used in the cross-sectional pricing regression:

$$r_{i,s}^e = a_{i,t} + \beta_{i,t}^\top f_s + \eta_{i,s}, \quad s = t - 756, \dots, t - 1,$$

where $r_{i,s}^e$ is the excess return on portfolio i and f_s is the six-factor vector. We retain the slope vector $\hat{\beta}_{i,t}$ and the residual variance $\hat{\sigma}_{i,t}^2$. These estimated exposures enter the date t cross-sectional pricing regressions used to estimate the common and group-specific risk prices in (2). This rolling-window beta implementation differs from the static-beta specification used in [Patton and Weller \(2022\)](#). The choice is natural in our setting because the object of interest is a daily time series of segmentation. Rolling exposures allow the cross-sectional pricing regressions to capture changes in factor loadings.

Given the factor exposures, we estimate the latent group assignments and the sequence of group-specific risk prices in (2). For a fixed number of groups G , we use the iterative estimator of [Patton and Weller \(2022\)](#). Conditional on group assignments, the problem reduces to weighted cross-sectional regressions estimated date by date. We premultiply each observation by $w_{i,t} = 1/\hat{\sigma}_{i,t}$, equivalent to inverse-variance WLS, so that portfolios

with noisier residual returns receive less weight. Conditional on the estimated risk prices, each portfolio is assigned to the group whose risk-price sequence best fits its return history. Iterating between these two steps delivers a local optimum of the grouped-pricing objective; we use multiple starting values to reduce sensitivity to initialization.

To assess whether the estimated groups capture genuine differences in factor risk prices, we test for out-of-sample heterogeneity using the minimal nontrivial alternative, $G = 2$. The daily sample is split into halves, with group assignments estimated on the first half and differences between groups tested on the second half. We consider two types of tests. The first tests for evidence of market segmentation, using the methods in [Patton and Weller \(2022\)](#). The second test is a novel bootstrap-based test for evidence of *time-varying* market segmentation. This test examines whether the observed time-series variation in (cross-group) differences in risk prices is too large to be consistent with a constant difference in risk prices. The test is described in detail in [Appendix A](#).

Table 3 presents the test results. We first test whether evidence of market segmentation exists across this sample of test assets using the “average” and “dynamic” tests presented in [Patton and Weller \(2022\)](#). Consistent with the results in that paper, in Panel A of Table 3 we see that we strongly reject the null of equal risk prices using both tests.

We next examine the proportion of per-period tests of market integration that reject the null, and find our first evidence of time-varying market segmentation. Panel B of Table 3 shows that on around one-fifth of dates we cannot reject the null of market integration even at the 10% significance level, while on nearly two-thirds of dates we can reject this null at the 1% significance level. Thus this market moves between dates on which equal risk prices cannot be rejected and dates on which segmentation is pronounced.

Table 3: **Testing for market segmentation.** Panel A reports the p -values from the “average” and “dynamic” tests of equal risk prices (i.e., no market segmentation) across groups proposed in [Patton and Weller \(2022\)](#). Panel B reports the proportion of dates for which the per-period “dynamic” test rejects the null of equal risk prices at three different significance levels. Panel C reports the p -value from a new test that the degree of market segmentation is constant over time.

<i>Statistic</i>	<i>Value</i>
Panel A: Tests of no market segmentation	
Equal average risk prices p -value	< 0.001
Equal risk prices per period p -value	< 0.001
Panel B: Per-period tests of equal risk prices	
Proportion with $p_t < 0.10$	0.806
Proportion with $p_t < 0.05$	0.748
Proportion with $p_t < 0.01$	0.622
Panel C: Test of constant market segmentation	
Constant market segmentation p -value	< 0.001

Finally we present the results of the new bootstrap test for constant market segmentation. Panel C of Table 3 shows that we reject the null of constant market segmentation at the 1% level. Thus, the U.S. equity market exhibits significant evidence of segmentation (Panel A) and significant evidence of time-varying segmentation (Panels B and C).

3.2 Estimating the number of groups

Having found significant evidence of market segmentation in the previous section, we now seek to determine the optimal number of clusters needed to fit our data. We consider $G \in \{1, 2, 3, 4, 5\}$. Group assignments are estimated on the first half of the dates, and holding those assignments fixed, we evaluate out-of-sample fit on the second half using five-

fold cross-sectional validation within each date. Specifically, for each date risk prices are estimated on 80% of the assets and pricing errors are evaluated on the remaining 20% of assets. The out-of-sample criterion is the sum of weighted squared pricing errors across folds and dates.

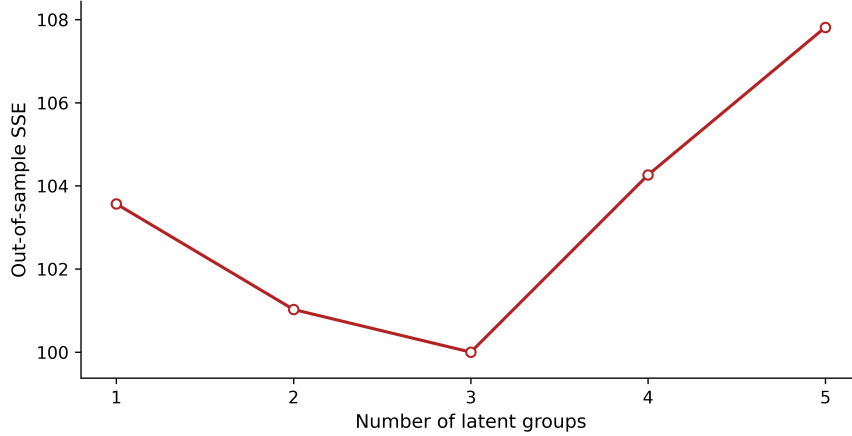
For each G , we use 100 starting values. For $G = 2$, all starts are random assignments. For larger values of G , half of the starts are random and half are “warm starts,” obtained by randomly splitting one group from the model with $G - 1$ groups. For $G > 2$, the lowest and near-lowest objective values are consistently obtained from these warm starts rather than from purely random starts, providing a useful diagnostic that the selected solutions are not driven by isolated random initializations. In all cases we impose a minimum group size equal to 10% of the test-asset universe.

Figure 1 reports the cross-validated pricing-error criterion across candidate values of G . We see that three groups provide the best out-of-sample fit, slightly better than two, and considerably better than four or five. After selecting G , we re-estimate the group assignments on the full sample using 100 random starts. The empirical analysis below holds these full-sample group assignments fixed and studies the time series of the resulting group-specific risk-price deviations.

The estimation method assigns portfolios to clusters using factor pricing behavior only. Supplemental Appendix S.1 reports the detailed group assignments and shows that the clearest *ex post* organizing dimension is market capitalization. Group 1 is the largest and broadest group, containing much of the middle of the size distribution and most of the industry portfolios, a “core market” cluster. Group 3 contains most portfolios in the second-smallest size quintile and has the highest average six-factor R^2 and lowest residual variance, a “small-cap core” cluster. Group 2 contains essentially all of the portfolios in the smallest size quintile, the characteristic extremes, and high-idiosyncratic-risk industries, a “speculative

Figure 1: **Cross-validated pricing-error criterion by number of latent groups.**

The figure reports the out-of-sample weighted squared pricing-error criterion for each candidate number of groups G . For each G , the plotted value is the lowest criterion value across initialization starts. The criterion is normalized by the overall minimum.



periphery” cluster. The partition is not a pure size classification: large-stock portfolios and characteristic extremes appear in all three groups. These labels are proffered only to make the latent groups less abstract.

3.3 An index of market segmentation

With the number of clusters and the cluster assignments determined using the methods described above, we obtain the estimated group-specific risk price for each group g and each date t :

$$\hat{\lambda}_{g,t} = \hat{\lambda}_{0,t} + \hat{d}_{g,t}. \quad (3)$$

The deviations from the baseline premia, $\hat{d}_{g,t}$, are the inputs to our index of market segmentation. For each factor k and date t , we measure factor-specific segmentation as the

cross-group dispersion of the factor-specific deviations:

$$\hat{\sigma}_{k,t} = \left(\frac{1}{G} \sum_{g=1}^G \hat{d}_{g,k,t}^2 \right)^{1/2}. \quad (4)$$

Recall that the deviations have a cross-group mean of zero, making $\hat{\sigma}_{k,t}$ the cross-group standard deviation of the risk prices for factor k . It is zero when all groups earn the same compensation for exposure to factor k and increases as the group-specific risk prices diverge. Section 4.1 below shows how this cross-group variation arises naturally in a preferred-habitat environment.

Because the group deviations are estimated, their raw cross-group dispersion contains both true risk-price heterogeneity and estimation error. Consider the $G \times 1$ vector of estimated deviations for factor k on date t ,

$$\hat{d}_{k,t} = d_{k,t}^* + \epsilon_{k,t}, \quad \mathbb{E}[\epsilon_{k,t} | \mathcal{F}_t] = 0, \quad \text{Cov}[\epsilon_{k,t} | \mathcal{F}_t] = \Sigma_{k,t}.$$

The squared segmentation index can then be decomposed as

$$\hat{\sigma}_{k,t}^2 = \frac{1}{G} \hat{d}_{k,t}^\top \hat{d}_{k,t} \quad (5)$$

$$= \frac{1}{G} d_{k,t}^{*\top} d_{k,t}^* + \frac{1}{G} \epsilon_{k,t}^\top \epsilon_{k,t} + \frac{2}{G} d_{k,t}^{*\top} \epsilon_{k,t}. \quad (6)$$

The first term is the true dispersion in risk prices, which is the object of interest. The third term cannot be estimated because it depends on the latent true deviations, but it has conditional mean zero, and so it represents measurement error. The second term generates a positive bias to the measured dispersion. Its conditional expectation is

$$\mathbb{E} \left[\frac{1}{G} \epsilon_{k,t}^\top \epsilon_{k,t} \mid \mathcal{F}_t \right] = \frac{1}{G} \text{tr}(\Sigma_{k,t}).$$

Using the covariance estimate $\widehat{\Sigma}_{k,t}$ obtained from the date-specific cross-sectional regression, we define the estimation-error-adjusted segmentation index as

$$\widehat{\sigma}_{k,t}^{adj} = \left[\frac{1}{G} \sum_{g=1}^G \widehat{d}_{g,k,t}^2 - \frac{1}{G} \text{tr} \left(\widehat{\Sigma}_{k,t} \right) \right]_+^{1/2} \quad (7)$$

where $[x]_+ \equiv \max\{x, 0\}$. This estimate is smaller than the simple standard deviation of estimated risk prices, and the adjustment automatically accommodates variation in measurement error, including variation associated with time-varying return volatility, as this is captured in $\widehat{\Sigma}_{k,t}$. We construct the daily aggregate segmentation index as the equal-weighted average of the factor-specific adjusted daily indices,

$$\widehat{\sigma}_{\text{Agg},t}^{adj} = \frac{1}{6} \sum_{k=1}^6 \widehat{\sigma}_{k,t}^{adj}. \quad (8)$$

For interpretability, we report segmentation measures in annualized two-standard-deviation spread units, multiplying the index in equations (7)-(8) by $2\sqrt{252}$. This reflects the spread between a relatively high-priced group (one standard deviation above the mean) and a low-priced group (one standard deviation below the mean). Clearly, this is merely a re-scaling and does not affect the information content of the index.

To obtain the monthly index, we average the daily estimation-error-adjusted variance within each calendar month, which reduces the impact of the zero-mean estimation-error component in equation (6), before applying the positive-part square root. For month m containing N_m daily observations, the monthly segmentation index for factor k is:

$$\widehat{\sigma}_{k,m}^{adj} = \left[\frac{1}{N_m} \sum_{t \in m} \left\{ \frac{1}{G} \sum_{g=1}^G \widehat{d}_{g,k,t}^2 - \frac{1}{G} \text{tr} \left(\widehat{\Sigma}_{k,t} \right) \right\} \right]_+^{1/2}. \quad (9)$$

We scale the resulting monthly index by the same $2\sqrt{252}$ factor used for the daily index,

so that both are reported in annualized two-standard-deviation spread units. The monthly aggregate index is constructed as the equal-weighted average of the six factor-specific monthly indices in equation (9).

Having constructed the segmentation index, we next examine its time-series behavior. Figure 2 reports the monthly aggregate index together with the six factor-specific indices. All seven series exhibit substantial time variation, although the levels and timing of the movements differ across factors. Several indices rise markedly around the late-1990s and early-2000s, the global financial crisis, the 2020 stress episode, and parts of the final years of the sample. The factor-specific panels therefore reveal both a common cyclical component and economically important heterogeneity in which risk prices become more segmented at a given time. Because the vertical axes are expressed in annualized two-standard-deviation spread units, a value of 10 corresponds to a 10 percentage point annualized spread in expected factor compensation between a group one standard deviation above the cross-group mean and a group one standard deviation below it.⁴

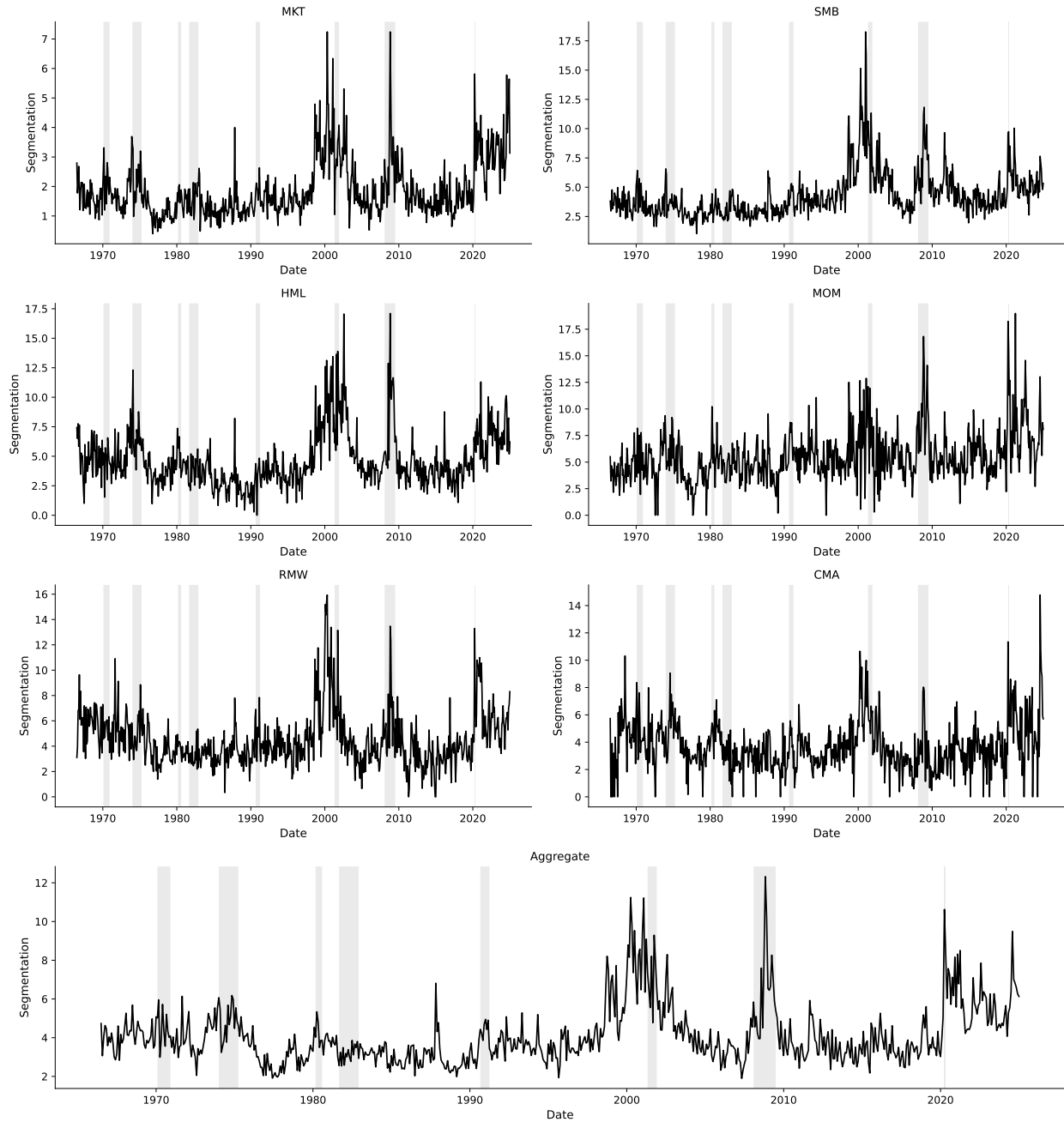
3.4 Market segmentation and maximum Sharpe ratios

We now examine whether the segmentation index is able to identify periods when allowing for group-specific pricing materially changes the investment opportunity set. We do so by estimating the improvements in Sharpe ratios from allowing for multiple clusters that are possible when segmentation is high versus low. For comparability with other analyses we compound daily returns and risk prices to monthly returns.

For each strategy and month, we estimate the mean vector and covariance matrix using the previous 252 daily observations ending at the prior month-end. The optimal portfolio

⁴We also computed the segmentation indices using $G = 2$ and $G = 4$. Relative to the $G = 3$ specification, the Aggregate index has correlations of 0.80 and 0.88 for $G = 2$ and $G = 4$, respectively. Across the six factor-specific indices, the corresponding correlations range from 0.29 to 0.89 for $G = 2$ and from 0.47 to 0.92 for $G = 4$.

Figure 2: **Factor-specific and aggregate monthly segmentation indices.** This figure presents the monthly segmentation indices for each factor and the aggregate segmentation index from January 1966 to December 2024. All series are expressed in annualized two-standard-deviation spread units. Shaded regions denote NBER recessions.



weights are

$$w_t \propto \hat{\Sigma}_t^{-1} \hat{\mu}_t,$$

and are rescaled to have an ex ante annualized volatility of 10%.⁵ The weights are held fixed over the next calendar month, and the realized monthly portfolio return is stored.

We compare the Sharpe ratios of portfolios constructed under the integrated model, which imposes a single price of risk, and the segmented model, which allows for clusters of risk prices. We stratify our sample period by our aggregate index of market segmentation on the last day of the previous month, so that month t returns are sorted using information from month $t - 1$. We divide months into terciles labelled Low, Medium, and High segmentation.

Note that this analysis is a frictionless opportunity-set comparison rather than an implementable trading strategy. In particular, the group assignments are estimated on the full sample. The question is whether allowing for group-specific risk prices expands the mean-variance opportunity set and whether the gains are concentrated when measured segmentation is high.

We test the null that the Sharpe ratio for the integrated model is weakly greater than that of the segmented model, against the alternative that the segmented model leads to a strictly higher Sharpe ratio. We implement the test using a studentized circular block bootstrap in the spirit of [Ledoit and Wolf \(2008\)](#). The bootstrap uses 1,999 resamples and a six-month block length, and preserves contemporaneous dependence between strategies. Appendix C gives the details.⁶

Table 4 reports that in high-segmentation periods, the segmented model portfolio attains an annualized Sharpe ratio of 1.15, compared with 0.78 for the integrated model portfolio,

⁵The volatility target puts the competing opportunity sets on a common risk scale, so that Sharpe-ratio comparisons are not driven by differences in unconditional volatility. This normalization is related in spirit to the volatility-managed portfolio comparisons of [Moreira and Muir \(2017\)](#), although our analysis uses the scaling only to compare estimated opportunity sets rather than to construct a volatility-timing strategy.

⁶The test of [Jobson and Korkie \(1981\)](#) with the correction of [Mommel \(2003\)](#) yields very similar results.

Table 4: **Sharpe ratios as a function of the degree of market segmentation.**

The table presents annualized Sharpe ratios from the model imposing an integrated market with a single cluster and from the model allowing for three clusters. Both portfolios are rescaled to a 10% annualized volatility target. The sample is split into terciles using the one-period-lagged segmentation index. The bottom row reports one-sided p -values from a studentized block bootstrap in the spirit of [Ledoit and Wolf \(2008\)](#), testing the null that the Sharpe ratio of the multiple-cluster portfolio is less than or equal to that of the single-cluster portfolio.

	<i>Market segmentation</i>		
	Low	Medium	High
Single cluster Sharpe ratio	0.920	1.310	0.780
Multiple cluster Sharpe ratio	1.050	1.490	1.150
Difference	0.130	0.180	0.370
p -value	0.149	0.166	0.028

and the one-sided bootstrap test rejects the null hypothesis. In the low- and medium-segmentation periods, the gains are smaller and not significantly different from zero. This provides further evidence, this time economic as opposed to statistical, of the time-varying nature of segmentation in this market.

4 Economic drivers of market segmentation

4.1 Preferred equity habitats

A popular model of fixed-income markets is one with “preferred habitats,” where investors in government bonds have demands for certain maturity segments, and arbitrageurs trade across those segments ([Modigliani and Sutch, 1966](#); [Vayanos and Vila, 2021](#)). [Greenwood et al. \(2018\)](#) extend this to consider an environment in which investors specialize in a single asset class and arbitrageurs trade across multiple classes. We adapt this logic to segments *within* the U.S. equity market where, in contrast to the single dimension of heterogeneity

(maturity) in the market for government bonds, habitats may form along multiple dimensions, including market capitalization, industry, growth prospects, cyclicalities, and trading liquidity. Such equity habitats are well documented: investors organize portfolios around styles or categories of stocks (Barberis and Shleifer, 2003; Froot and Teo, 2008; Wahal and Yavuz, 2013); reclassification across categories can change a stock’s comovement and clientele without changing its fundamentals (Barberis et al., 2005; Greenwood, 2008); and holdings data reveal persistent heterogeneity in institutional demand across regions of the cross section (Gompers and Metrick, 2001; Kojien and Yogo, 2019).

We interpret the latent pricing clusters estimated in the previous section as habitats: regions of the cross section in which investor clienteles create group-level factor-risk imbalances.⁷ Arbitrageurs can trade across habitats and compress differences in the compensation attached to the same factor exposure, but only imperfectly when the trade is risky or costly to intermediate.

Let $\lambda_{g,t}$ denote the K -dimensional price of factor risk in group g at date t . We decompose it into a common component and a group-specific deviation,

$$\lambda_{g,t} = \lambda_{0,t} + d_{g,t}, \quad \text{where} \quad \frac{1}{G} \sum_{g=1}^G d_{g,t} = 0.$$

Each group can be interpreted as a habitat with a natural investor clientele. Preferred-habitat investors create group-level factor-risk imbalances. Let $s_{g,t}$ denote the K -dimensional net factor-risk imbalance in group g . Common imbalances affect the common price of risk, $\lambda_{0,t}$. Segmentation is driven by imbalances relative to the cross-group average:

$$\bar{s}_t = \frac{1}{G} \sum_{g=1}^G s_{g,t} \quad \text{and} \quad \tilde{s}_{g,t} = s_{g,t} - \bar{s}_t. \quad (10)$$

⁷There are likely many more “equity habitats” than those that generate differences in risk prices. Our focus is on the aggregation of these habitats into clusters that have distinct prices of factor risk.

We assume a single representative arbitrageur who can trade across habitats. Let $x_{g,t}$ denote the arbitrageur's position in the factor-risk exposure of group g . We assume that the arbitrageur takes long-short positions across groups and holds zero net factor exposures. This implies:

$$\frac{1}{G} \sum_{g=1}^G x_{g,t} = 0.$$

Let $c_{g,t}$ denote the signed per-unit intermediation cost in group g , capturing transaction costs, funding costs, liquidity costs, and other implementation frictions in reduced form. Let $\gamma > 0$ denote the mean-variance risk aversion parameter for the arbitrageur, and let Ω_t be the conditional covariance matrix of unhedgeable basis risk in the relative cross-habitat trade. We keep γ fixed, so time variation in segmentation does not arise from changes in preferences. The arbitrageur then solves

$$\max_{\{x_{g,t}\}_{g=1}^G} \frac{1}{G} \sum_{g=1}^G \left[x_{g,t}^\top (\lambda_{0,t} + d_{g,t} - c_{g,t}) - \frac{\gamma}{2} x_{g,t}^\top \Omega_t x_{g,t} \right] \quad \text{subject to} \quad \frac{1}{G} \sum_{g=1}^G x_{g,t} = 0. \quad (11)$$

The first-order condition implies

$$d_{g,t} = \gamma \Omega_t x_{g,t} + \tilde{c}_{g,t} \quad (12)$$

$$\text{where} \quad \tilde{c}_{g,t} = c_{g,t} - \bar{c}_t, \quad \text{and} \quad \bar{c}_t = \frac{1}{G} \sum_{g=1}^G c_{g,t}. \quad (13)$$

Market clearing in relative exposures requires $x_{g,t} = \tilde{s}_{g,t}$, which implies that the group-specific risk-price deviation is

$$d_{g,t} = \gamma \Omega_t \tilde{s}_{g,t} + \tilde{c}_{g,t}.$$

The first term on the right-hand side is the risk-bearing channel: arbitrageurs require compensation for holding relative factor-risk imbalances because exposures in different habitats are not perfect substitutes. Even if two habitats load on the same factor, the relative trade

can carry basis risk, liquidity risk, and implementation risk that cannot be fully hedged. The second term is the intermediation-cost channel: segmentation can arise when trading, liquidity, or funding costs differ across groups.

The factor- k risk-price deviation for group g is

$$d_{g,k,t} = \mathbf{e}_k^\top d_{g,t} = \gamma \mathbf{e}_k^\top \Omega_t \tilde{s}_{g,t} + \tilde{c}_{g,k,t}, \quad (14)$$

where $\mathbf{e}_k$ denotes the k th unit vector. Our focus is on the cross-group variation in risk prices, measured as:

$$\sigma_{k,t}^2 = \frac{1}{G} \sum_{g=1}^G d_{g,k,t}^2 \quad (15)$$

Substituting in the solution for $d_{g,k,t}$ from the above equation yields:

$$\sigma_{k,t}^2 = \gamma^2 \frac{1}{G} \sum_{g=1}^G (\mathbf{e}_k^\top \Omega_t \tilde{s}_{g,t})^2 + \frac{1}{G} \sum_{g=1}^G \tilde{c}_{g,k,t}^2 + 2\gamma \frac{1}{G} \sum_{g=1}^G (\mathbf{e}_k^\top \Omega_t \tilde{s}_{g,t}) \tilde{c}_{g,k,t}. \quad (16)$$

Appendix D presents further details on the derivation. The framework does not require all three channels to operate simultaneously. Time-varying relative demand imbalances generate segmentation whenever the cross-habitat position carries basis risk; dispersion in intermediation costs can generate segmentation even when the risk-bearing component is small; and changes in basis risk amplify or attenuate a given set of relative imbalances. The interaction term further implies that demand pressure and intermediation costs can reinforce or offset one another. The model is too stylized to identify these primitives separately, but it disciplines the interpretation of the regression analysis below and clarifies that common market-wide movements belong to the common risk price, whereas segmentation is generated by cross-habitat differences.

4.2 Proxies for the drivers of market segmentation

The underlying drivers of varying market segmentation in the model are not observable, and instead we consider a variety of macro-financial state variables as proxies. The variables in the first group proxy for relative factor-risk imbalances, $\tilde{s}_{g,t}$. Valuation conditions and recent market performance can shift investor demand across habitats and change the relative amount of factor exposure that arbitrageurs must absorb. [Bekaert and Harvey \(1995\)](#) show that market integration varies with market conditions and valuation states. We therefore include the DJIA book-to-market ratio, a standard valuation variable in the equity-premium literature following [Welch and Goyal \(2008\)](#), and the three-year up-market indicator of [Cooper et al. \(2004\)](#). The model does not imply a universal coefficient sign for these proxies: the segmentation index depends on the magnitude and cross-group pattern of relative imbalances rather than on the direction of an aggregate valuation state. Their coefficients should consequently be interpreted as reduced-form associations rather than structural comparative statics.

The second group is aimed at funding-related variation in Ω_t and $\tilde{c}_{g,t}$. Models of intermediary asset pricing and constrained arbitrage, including [Brunnermeier and Pedersen \(2009\)](#), [He and Krishnamurthy \(2013\)](#), [Gârleanu and Pedersen \(2011\)](#), and [Gromb and Vayanos \(2018\)](#), imply that the availability and cost of balance-sheet capacity affect the ability of arbitrageurs to compress pricing wedges. In the model, tighter funding conditions can make the relative cross-habitat trade riskier, increasing the relevant basis-risk component Ω_t , and can also raise the cost of intermediating positions in particular habitats, increasing the dispersion of $\tilde{c}_{g,t}$. We use the TED spread and the three-month Treasury bill rate as funding proxies.^{8,9}

⁸The FRED TED spread series is available from January 2, 1986 until January 21, 2022. We extend the series thereafter using SOFR minus the three-month Treasury bill rate as a short-term funding-spread proxy.

⁹We note that these are aggregate measures: if funding markets are themselves segmented, as found by [Siriwardane et al. \(2025\)](#), aggregate funding spreads may capture the habitat-specific funding costs embedded

The third group is aimed at trading pressure and intermediation-cost dispersion. Detrended aggregate S&P 500 trading volume proxies for the quantity of order flow and factor exposure that intermediaries must absorb and therefore maps most naturally to relative imbalances, $\tilde{s}_{g,t}$. Market-liquidity measures map more directly to the intermediation-cost term, $\tilde{c}_{g,t}$: when liquidity is poor, trading across habitats is more costly and those costs may differ more across groups. We adopt S&P 500 trading volume, S&P 500 [Amihud \(2002\)](#) illiquidity, and the [Pastor and Stambaugh \(2003\)](#) aggregate liquidity series, the latter sign-flipped so that higher values correspond to poorer liquidity. Under these conventions, positive coefficients on volume and illiquidity indicate wider segmentation when trading pressure is elevated or market liquidity deteriorates.

The fourth group is aimed at sentiment-driven variation in relative imbalances, $\tilde{s}_{g,t}$. Disagreement, subjective valuation, and limits to arbitrage, as in [Miller \(1977\)](#) and [Baker and Wurgler \(2006\)](#), can shift investor demand across habitats and make pricing wedges more persistent. We include the Baker-Wurgler sentiment index and Michigan consumer sentiment as sentiment-related proxies for variation in relative demand pressure across habitats. As with valuation variables, the sign is not pinned down ex ante because sentiment can either compress or amplify relative demand imbalances depending on which habitats are most affected.

The fifth group is aimed at uncertainty-driven variation in basis risk, Ω_t . When financial uncertainty is high, the relative cross-habitat trade is riskier because exposures in different habitats are less reliable substitutes and the residual component of the relative trade is harder to hedge. We use the financial uncertainty index of [Jurado et al. \(2015\)](#) and changes in $\log(\text{VIX})$ as proxies for time variation in Ω_t .

Finally, we include the NBER recession indicator as a broad stress indicator, indicating

in $\tilde{c}_{g,t}$ only imperfectly, and weak explanatory power for these proxies need not indicate that funding frictions are unimportant.

periods in which relative imbalances may be larger, intermediation costs may be higher, and basis risk in the relative cross-habitat trade may increase.

4.3 State dependence of the segmentation index

We first provide descriptive evidence on the relation between segmentation and selected state variables, reporting the correlation between the monthly aggregate segmentation index and a set of trading activity, market liquidity, and funding-related variables. Table 5 shows that the market segmentation index is not highly correlated with any single state variable. The two largest correlations are with the two measures of market illiquidity, [Pastor and Stambaugh \(2003\)](#) and [Amihud \(2002\)](#), at 0.21 and 0.16. The positive correlation with volume, 0.15, is consistent with segmentation being greater when intermediaries must absorb greater trading pressure. Correlations with measures of funding liquidity, the TED spread and the three-month Treasury bill rate, are close to zero, at -0.01 and 0.03 . The corresponding daily correlations are similarly modest and are reported in Supplemental Table S.6.

Guided by the decomposition in Section 4.1, we next use regressions of segmentation on the proxies for relative factor-risk imbalances, intermediation cost dispersion, and basis risk. We conduct the regression on both the daily and monthly segmentation indices, and because the state vectors are aligned contemporaneously with the segmentation measure, a positive coefficient indicates that measured segmentation is wider in that state. For the monthly regressions, the time-series transformation of each state variable is determined first, including differencing or detrending where needed to induce stationarity (see Table 2), and the subsequent monthly aggregation reflects the variable’s native sampling frequency. The TED spread, Treasury-bill rate, detrended trading volume, detrended Amihud illiquidity, and change in log VIX are observed daily and we average their transformed daily values within calendar months. Financial uncertainty, Pastor–Stambaugh illiquidity, the NBER

Table 5: **Correlation between segmentation and selected state variables.**

This table reports the correlation between the monthly aggregate segmentation index described in Section 3.3 and a subset of the variables described in Section 4.2. The Pastor-Stambaugh series is sign-flipped so that higher values indicate greater market illiquidity.

	Dispersion	Amihud	P&S	Volume	VIX	TED
Amihud illiquidity	0.16					
P&S illiquidity	0.21	0.19				
Trading volume	0.15	0.02	0.01			
VIX	-0.07	0.12	0.01	-0.07		
TED spread	-0.01	0.13	0.06	0.04	-0.02	
T-bill rate	0.03	-0.14	-0.05	-0.05	0.02	-0.77

recession indicator, the DJIA book-to-market ratio, Michigan sentiment, and Baker–Wurgler sentiment are observed only monthly and are forward-filled only to align them with the daily regressions; for the monthly regressions, we use the latest available monthly observation. The three-year up-market indicator (Cooper et al., 2004) is observed daily and uses its final value within the month so that it remains in zero-one units. Continuous state variables are standardized separately for the daily and monthly regressions, while the indicator variables are not standardized. In addition to OLS, we use the LASSO to identify the most important variables, and then use OLS on the subset of selected variables, making this “post-LASSO” estimation. The LASSO regularization parameter is chosen using five contiguous time-series cross-validation blocks.

To test the significance of the regressions, we use a stationary bootstrap (Politis and Romano, 1994) placebo design which accounts for persistence and contemporaneous cross-correlation in the state variables.¹⁰ We apply the bootstrap separately to the segmentation index and the regressors, so that the true explanatory power of the regression in the bootstrap world is zero, thereby allowing us to test the significance of the observed explanatory power.

¹⁰The daily bootstrap uses an expected block length of 63 trading days, while the monthly bootstrap uses an expected block length of three months. We use 1,000 draws at each frequency.

Table 6: **Joint significance of the regressions.** The table reports results from regressions of the indices of market segmentation introduced in Section 3.3 on the twelve variables described in Section 4.2. R^2 values are in percent. The p -value for the significance of the regression is based on a stationary bootstrap applied separately to the segmentation index and the set of regressors. The rows contain the six factor-specific segmentation indices and the aggregate index. The sample period is January 1986 to December 2024.

<i>Factor</i>	OLS				Post-LASSO OLS			
	<i>Daily</i>		<i>Monthly</i>		<i>Daily</i>		<i>Monthly</i>	
	R^2	p -value	R^2	p -value	R^2	p -value	R^2	p -value
MKT	5.4	0.001	20.7	0.004	5.4	0.001	20.7	0.002
SMB	6.8	0.001	30.0	0.001	6.8	0.001	30.0	0.001
HML	5.3	0.001	23.7	0.002	0.0	—	9.8	0.015
MOM	4.6	0.001	26.3	0.001	4.6	0.001	26.3	0.001
RMW	4.7	0.001	22.3	0.001	4.7	0.001	22.3	0.001
CMA	2.9	0.001	13.9	0.003	2.6	0.001	12.9	0.001
Aggregate	13.0	0.001	30.7	0.001	12.9	0.001	30.7	0.001

The regression p -value is computed as the proportion of bootstrap regressions with an R^2 at least as large as that observed in the data. For the post-LASSO regressions, selection is performed once using the observed data, and the selected variables are held fixed across the placebo regressions.

Table 6 shows that the collection of regressors explains between 3% and 7% of variation in the daily factor-specific segmentation indices, and 13% of the variation in the daily aggregate index. The values are almost identical when using post-LASSO OLS except for the HML index, where the LASSO selects no regressors and the R^2 then drops from around 5% to zero. In all cases aside from that one, the p -values for the regression strongly reject the null of zero explanatory power. Consistent with the monthly indices averaging out the estimation error in the daily indices (recall Section 3.3), the R^2 values for the monthly regressions are substantially larger, ranging from about 10% to 31%. The state variables therefore align

more closely with the lower-frequency component of segmentation than with its day-to-day variation. We focus on the monthly post-LASSO estimates below.

Table 7 reports the post-LASSO regression for the monthly segmentation indices. The post-LASSO specification provides a (somewhat) more parsimonious representation of these relations, retaining only the variables that survive regularization by the LASSO.¹¹ Because the dependent variables are expressed in annualized two-standard-deviation units, a coefficient of 0.10 corresponds to a 10-basis-point change in the annualized cross-group spread.

The clearest pattern in Table 7 concerns market trading conditions. Amihud illiquidity is positive and significant for all six factor-specific indices and for the aggregate index. For the aggregate index, the coefficient is 0.49, implying that a one-standard-deviation increase in Amihud illiquidity is associated with a 49-basis-point increase in the annualized cross-group spread. Detrended aggregate S&P 500 trading volume is positive and significant for MKT, SMB, MOM, RMW, and the Aggregate.

The remaining monthly relations are less pervasively significant. The three-year up-market indicator (UP) is negative and significant for MKT, SMB, and the Aggregate, while the recession indicator is positive and significant for MOM, RMW, and the Aggregate. Changes in the TED spread are negative and significant for SMB and the Aggregate, while changes in log VIX are negative and significant for SMB, MOM, RMW, and the Aggregate. HML provides a particularly parsimonious case: LASSO selects only Amihud illiquidity, which enters positively with a coefficient of 0.82. The remaining variables are often selected by LASSO but not generally significant.¹²

Figure 3 displays the monthly segmentation index and the corresponding OLS fitted

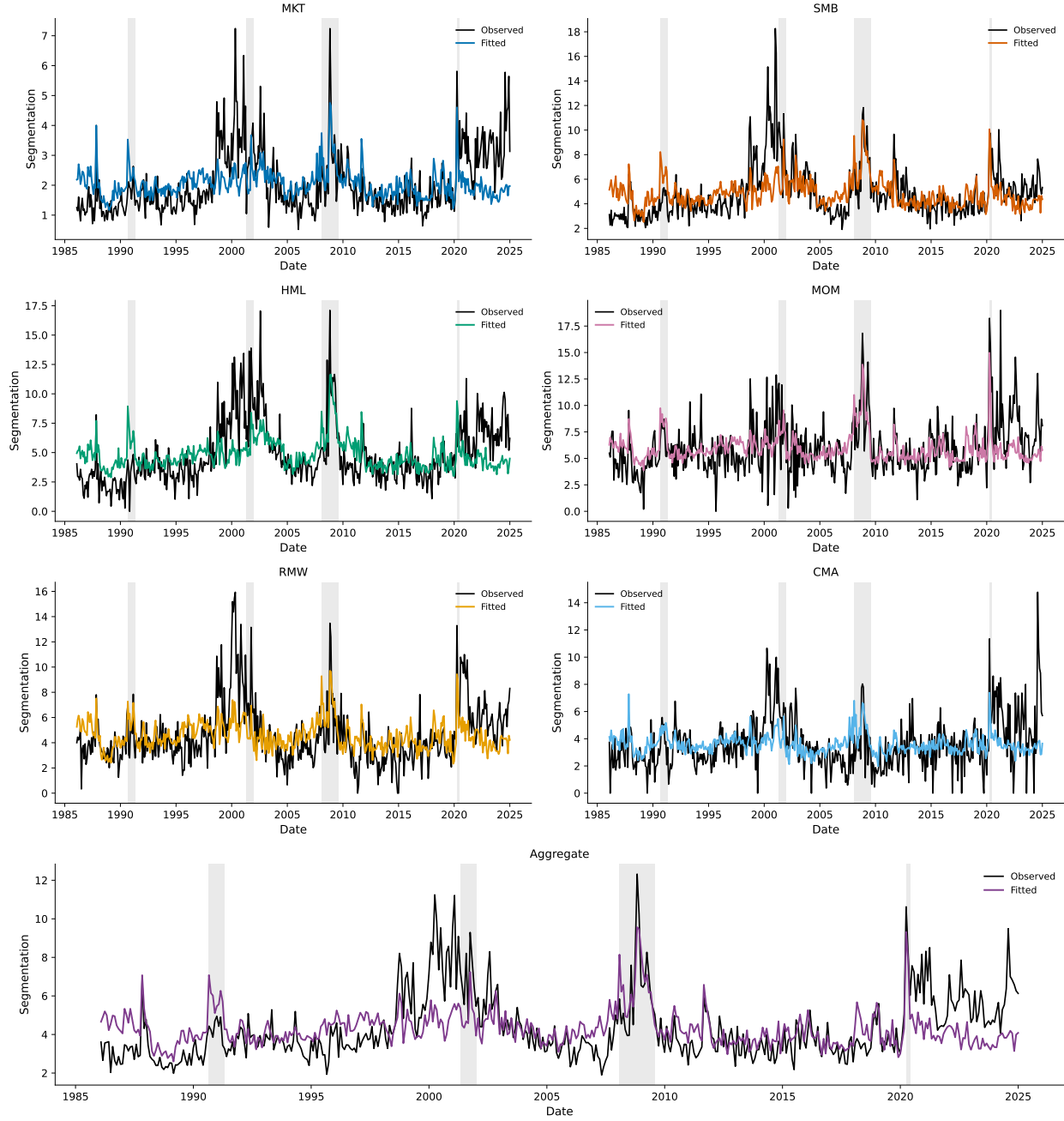
¹¹Results using OLS, without LASSO regularization, are presented in the supplemental appendix, along with corresponding results using the daily segmentation indices.

¹²We find similar results for regressions using the daily segmentation indices. Detrended trading volume and Amihud illiquidity are positive and significant for five factor-specific indices and for the aggregate. The recession indicator is positive and significant for MKT, SMB, MOM, RMW, and the aggregate. No state variables are selected for HML.

Table 7: **Post-LASSO regression results.** This table reports OLS estimates after LASSO variable selection for the six factor-specific segmentation indices and the aggregate index, at the monthly frequency. An empty cell indicates that the variable was not selected. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2.

	MKT	SMB	HML	MOM	RMW	CMA	Agg.
TED spr	-0.016 (0.050)	-0.166* (0.104)		-0.233 (0.124)	-0.173 (0.122)		-0.140* (0.082)
T-bill	-0.113 (0.070)	-0.298 (0.142)		-0.106 (0.155)	-0.123 (0.162)	-0.241 (0.107)	-0.157 (0.114)
Volume	0.259** (0.082)	0.485** (0.173)		0.559*** (0.171)	0.828*** (0.185)	0.236 (0.123)	0.483*** (0.135)
Fin uncert	-0.074 (0.072)	-0.083 (0.154)		0.079 (0.167)	-0.244 (0.171)		-0.105 (0.122)
PS illiq		0.172 (0.119)		0.092 (0.142)	0.115 (0.133)	0.165 (0.102)	0.134 (0.095)
Amihud	0.283*** (0.080)	0.439*** (0.167)	0.816** (0.176)	0.749*** (0.175)	0.541*** (0.177)	0.444*** (0.128)	0.490*** (0.132)
Recession	0.226 (0.360)	1.354 (0.742)		2.279*** (0.742)	1.389* (0.803)		1.232* (0.592)
BM ratio		-0.073 (0.113)			-0.067 (0.132)	-0.148* (0.099)	-0.051 (0.092)
UP	-0.655** (0.249)	-1.614*** (0.506)		-0.322 (0.533)	-0.530 (0.578)		-0.845** (0.415)
VIX	-0.023 (0.043)	-0.234*** (0.089)		-0.188* (0.106)	-0.155* (0.100)		-0.085* (0.067)
Mich sent	-0.035 (0.047)	-0.086 (0.091)			-0.139 (0.109)		-0.062 (0.074)
BW sent	0.080 (0.059)	0.373* (0.125)		0.110 (0.143)	0.330 (0.138)	0.206 (0.102)	0.193 (0.100)
R^2	0.207	0.300	0.098	0.263	0.223	0.129	0.307
p -value	0.002	0.001	0.015	0.001	0.001	0.001	0.001

Figure 3: **Observed and fitted segmentation indices.** The figure reports the observed monthly segmentation index and the fitted value from the OLS regression for each of the six factors and the aggregate. All series are expressed in annualized two-standard-deviation spread units, measured in percentage points. Shaded regions denote NBER recessions. The sample period is January 1986 to December 2024.



value. For several factors, both observed and fitted segmentation rise around the global financial crisis and the COVID-19 recession. However, segmentation is substantially higher than predicted by the regression model during the dot-com bubble of the late 1990s and in the few years following the COVID-19 recession. Looking across the factor segmentation indices, we see that SMB, HML and RMW segmentation peaked around the dot-com bubble, while MKT segmentation was slightly higher in the global financial crisis. MOM segmentation peaked around the COVID-19 crisis, while CMA segmentation peaked in July 2024, coinciding with earnings reports from the largest technology firms, whose large capital expenditures were under scrutiny. Such scrutiny is a natural stressor for an investment-factor index.

4.4 The persistence of market segmentation

The preceding regressions characterize the macro-financial states associated with the level of market segmentation. We next investigate the persistence of segmentation, and whether persistence varies with market conditions. This provides a complementary perspective on the preferred-habitat interpretation: a state variable may widen segmentation contemporaneously without necessarily making the resulting pricing differences more persistent.

The segmentation indices described in Section 3.3 are estimated quantities and their associated measurement error can attenuate conventional autoregressive estimates. We address this using the instrumental variables approach of [Hansen and Lunde \(2014\)](#), which uses more distant lags of the observed series as instruments to estimate the first-order autocorrelation of the underlying latent segmentation process. Note that this is distinct from the adjustment in Section 3.3; that adjustment corrects the level of the segmentation index for estimation error, while the Hansen-Lunde method addresses attenuation in the observed autocorrelation due to the presence of estimation error.

The top row of Table 8 presents estimates of autocorrelation using the instrumental variables approach of Hansen and Lunde (2014)¹³ and shows that the monthly segmentation indices are highly persistent. The autocorrelation estimates range from 0.87 for MOM to 0.97 for SMB, and the Aggregate estimate is 0.95, corresponding to a half-life of approximately 12 months. For comparison, the conventional OLS AR(1) estimate for the Aggregate is 0.76, so correcting for measurement error materially increases the estimated persistence.¹⁴

We next allow the persistence of market segmentation to vary with a state variable:

$$\rho_t = \bar{\rho} + \gamma Z_{t-1} \quad (17)$$

This model can be estimated using a simple GMM-based extension of Hansen and Lunde (2014), described in detail in Appendix E. We de-mean the state variable so that the intercept of this specification is interpretable as the average level of autocorrelation. We estimate this model separately for each state variable in Table 2.¹⁵ As in the regression analysis in the previous section, continuous state variables are standardized, while the NBER recession and up-market indicators remain in zero-one units.

The results of the time-varying persistence model are presented in the lower panel of Table 8. The state interactions reveal that the macro-financial states associated with the *persistence* of segmentation need not coincide with those associated with its level, reported in Table 7. The clearest example is trading volume. In Table 7, higher trading volume is associated with a higher level of Aggregate segmentation, and in Table 8 we observe it is also

¹³We use the “optimal instrument” estimator from Theorem 3 of Hansen and Lunde (2014), with lags two to eight as instruments.

¹⁴The procedure of Hansen and Lunde (2014) also yields an estimate of the contribution of estimation error to the variance of the observed series. The estimated shares range from 5% to 30%, with a value of 13% for the Aggregate index. For comparison, the corresponding shares for the daily segmentation indices range from 64% for the Aggregate index to 89% for the MOM index. This is consistent with within-month averaging mitigating the impact of estimation error.

¹⁵It is simple to accommodate multiple state variables at once, but, consistent with the caution in Hansen and Lunde (2014, Section 2.4), we are skeptical about finite-sample reliability with many estimated parameters, and so we do not consider more than one state variable at a time.

Table 8: **Persistence of segmentation indices.** The first row of this table reports the Hansen and Lunde (2014) estimate of the first-order autocorrelation of each segmentation index (across the columns) using lags 2-8 as instruments. The remaining rows of the table present the coefficients when the autocorrelation coefficient is assumed to vary with the state variable given in the row, as described in Appendix E. Each state variable is considered separately. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard errors. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The sample period is January 1986 to December 2024.

	MKT	SMB	HML	MOM	RMW	CMA	Agg.
$\bar{\rho}$	0.949 (0.014)	0.968 (0.011)	0.959 (0.015)	0.870 (0.031)	0.941 (0.016)	0.902 (0.030)	0.946 (0.015)
TED spr	0.025 (0.026)	0.043*** (0.008)	0.081*** (0.013)	0.019 (0.016)	-0.039** (0.016)	-0.032 (0.028)	0.070*** (0.006)
T-bill	-0.034 (0.025)	0.054*** (0.014)	0.023 (0.014)	0.074** (0.030)	0.016 (0.021)	0.033* (0.019)	0.001 (0.013)
Volume	-0.020 (0.022)	-0.022 (0.021)	-0.223*** (0.051)	-0.101* (0.054)	0.028 (0.031)	-0.059 (0.047)	-0.230*** (0.067)
Fin uncert	-0.023 (0.032)	-0.032 (0.020)	-0.028** (0.014)	-0.047** (0.019)	-0.011 (0.012)	-0.021* (0.013)	-0.011 (0.012)
PS illiq	0.009 (0.017)	0.040*** (0.012)	0.051*** (0.015)	-0.027 (0.039)	0.126*** (0.025)	-0.057* (0.030)	0.116*** (0.020)
Amihud	-0.010 (0.020)	0.031 (0.022)	0.013 (0.009)	0.054** (0.027)	0.033 (0.027)	-0.050*** (0.014)	-0.005 (0.008)
Recession	0.690** (0.278)	-0.096*** (0.031)	0.080** (0.037)	-0.037 (0.052)	-0.031 (0.047)	-0.094 (0.073)	0.030 (0.027)
BM ratio	-0.110** (0.043)	0.141*** (0.051)	0.254*** (0.082)	-0.033 (0.037)	0.341** (0.171)	-0.078* (0.043)	0.036 (0.042)
UP	-0.035 (0.034)	-0.001 (0.023)	0.088*** (0.031)	0.058 (0.062)	-0.259* (0.142)	0.236** (0.119)	-0.055* (0.032)
VIX	0.172*** (0.045)	0.091*** (0.035)	0.054 (0.063)	-0.046 (0.047)	0.079 (0.052)	0.262*** (0.088)	-0.049 (0.034)
Mich sent	-0.028 (0.048)	0.047** (0.019)	0.199*** (0.036)	0.107** (0.042)	0.124*** (0.039)	0.021 (0.088)	0.175*** (0.056)
BW sent	-0.154*** (0.021)	0.021*** (0.008)	0.133*** (0.027)	-0.165*** (0.063)	0.048** (0.021)	-0.011 (0.016)	-0.024*** (0.009)

associated with significantly lower persistence, with a coefficient of -0.23 . This pattern is consistent with elevated trade volume representing episodes of trading pressure that widen segmentation but dissipate relatively quickly.

The liquidity measures provide another distinction between the level and persistence of segmentation. Table 7 shows Amihud illiquidity is positive and significant for the level of all six factor-specific indices and the Aggregate index, but Table 8 reveals that its persistence effects are mixed across factors and essentially zero for the Aggregate. Pastor-Stambaugh illiquidity, by contrast, is not statistically significant for the level of Aggregate segmentation but is positive and highly significant for its persistence, as well as for SMB, HML, and RMW, consistent with some liquidity conditions operating more through the speed at which arbitrageurs can compress existing wedges than through their initial magnitude.

The TED spread provides a similar distinction: it is positive and significant for persistence in SMB, HML, and the Aggregate despite its relatively weak and predominantly negative relation with the level of segmentation. In the preferred-habitat framework, this is consistent with funding conditions affecting the ability and cost of intermediating relative cross-habitat positions, and hence the rate at which existing segmentation dissipates, even when they are not an important contemporaneous source of wider wedges.

Michigan consumer sentiment also has a broad positive association with persistence, entering positively and significantly for SMB, HML, MOM, RMW, and the Aggregate. Since we interpret sentiment as a proxy for relative investor demand across habitats, this result suggests that sentiment-related demand conditions may also matter for how quickly existing pricing differences are arbitrated away. Overall, the results reinforce the distinction between states that widen segmentation and states that determine how quickly the resulting differences in factor risk prices subsequently dissipate.

Table 9: **Testing for market segmentation, three-factor model.** Panel A reports the p -values from the “average” and “dynamic” tests of equal risk prices (i.e., no market segmentation) across groups proposed in [Patton and Weller \(2022\)](#). Panel B reports the proportion of dates for which the per-period “dynamic” test rejects the null of equal risk prices at three different significance levels. Panel C reports the p -value from a new test that the degree of market segmentation is constant over time. This table reports results for the three-factor model as well as the six-factor model as in Table 3.

<i>Statistic</i>	<i>Three factors</i>	<i>Six factors</i>
Panel A: Tests of no market segmentation		
Equal average risk prices p -value	< 0.001	< 0.001
Equal risk prices per period p -value	< 0.001	< 0.001
Panel B: Per-period tests of equal risk prices		
Proportion with $p_t < 0.10$	0.774	0.806
Proportion with $p_t < 0.05$	0.715	0.748
Proportion with $p_t < 0.01$	0.595	0.622
Panel C: Test of constant market segmentation		
Constant market segmentation p -value	< 0.001	< 0.001

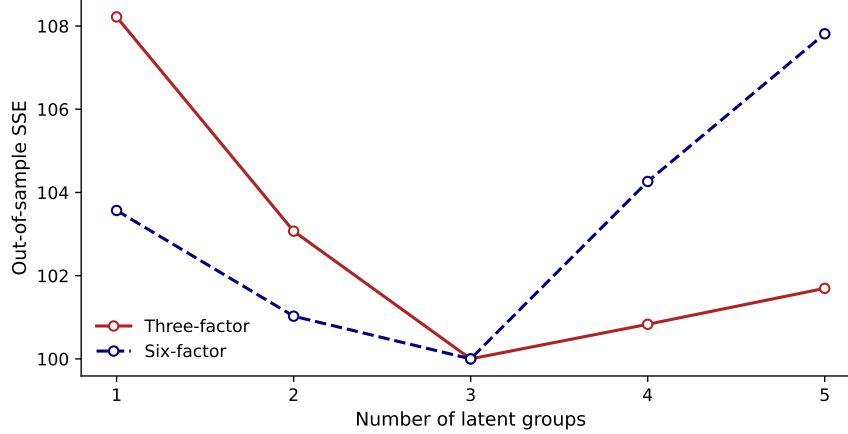
5 Robustness analysis

Our main analysis uses the six-factor model drawing on [Fama and French \(2015\)](#) and [Carhart \(1997\)](#). In this section we swap that model for the simpler three-factor model of [Fama and French \(1993\)](#), which uses the MKT, SMB and HML factors. We follow all of the same empirical steps as for the six-factor model: rolling-window factor exposure estimation, latent group assignment estimation, etc.

Table 9 shows that the split-sample tests continue to strongly reject market integration, with p -values less than 0.01. The per-period results are similarly strong: market integration is rejected on 77% of dates at the 10% level, 72% at the 5% level, and 60% at the 1% level.

Figure 4: **Cross-validated pricing-error criterion by number of latent groups.**

This figure reports the out-of-sample weighted squared pricing-error criterion for each candidate number of groups G under the three-factor (solid line) and six-factor (dashed line) specifications. For each specification and each G , the plotted value is the lowest criterion value across initialization starts. Each series is normalized by the overall minimum.



These frequencies are slightly lower than the corresponding six-factor frequencies of 81%, 75%, and 62%. Finally, the test for a constant degree of market segmentation, reported in Panel C of Table 9, again rejects the null with a p -value less than 0.01. Thus, the evidence of market segmentation, and time-varying market segmentation, is not sensitive to this change to the factor-model specification.

We next estimate the number of latent groups in the model with three factors. Figure 4 compares the cross-validated pricing-error criterion under the three-factor benchmark with that from the six-factor baseline. Both criteria are minimized at $G = 3$. Under the three-factor specification, the second-best model has four clusters rather than two as in the six-factor specification, consistent with the cross-validation method penalizing additional clusters less heavily when each cluster has three, rather than six, risk prices to estimate.

Table 10 considers the explanatory power of the twelve macro-financial state variables in Section 4.3 for the segmentation indices constructed using the three-factor model. The

Table 10: **Joint significance of the regressions, three-factor model.** The table reports results from regressions of the indices of market segmentation introduced in Section 3.3 on the twelve variables described in Section 4.2. R^2 values are in percent. The p -value for the significance of the regression is based on a stationary bootstrap applied separately to the segmentation index and the set of regressors. The rows contain the three factor-specific segmentation indices and the aggregate index, analogous to the results based on a six-factor model presented in Table 6. The sample period is January 1986 to December 2024.

<i>Factor</i>	OLS				Post-LASSO OLS			
	<i>Daily</i>		<i>Monthly</i>		<i>Daily</i>		<i>Monthly</i>	
	R^2	p -value	R^2	p -value	R^2	p -value	R^2	p -value
MKT	8.0	0.001	28.5	0.001	8.0	0.001	28.5	0.001
SMB	6.1	0.001	31.0	0.001	6.1	0.001	31.0	0.001
HML	5.5	0.001	22.8	0.001	5.5	0.001	22.8	0.001
Aggregate	11.9	0.001	33.3	0.001	11.9	0.001	33.3	0.001

results are very similar to those for the indices based on the six-factor model, reported in Table 6. The explanatory power for the daily segmentation indices ranges from 5.5% to 12%, and is in all cases significantly greater than zero. Explanatory power is substantially greater for the monthly segmentation indices, ranging from 23% to 33%. The results are thus very similar to those obtained using the six-factor model.

Next, we consider the regression coefficients for the segmentation indices constructed under the three-factor model, reported in Table 11. As for the results based on the six-factor model, reported in Table 7, Amihud illiquidity has a positive and significant coefficient for all individual factor segmentation indices and the aggregate index. Trading volume is likewise positive and significant for all three factor-specific indices and the Aggregate; in the six-factor analysis it is significant for MKT, SMB, MOM, RMW, and the Aggregate. The three-year up-market indicator is negative and significant for all four indices in the three-factor analysis, compared with MKT, SMB, and the Aggregate in the six-factor analysis.

Table 11: **Regression results, three-factor model.** This table reports OLS estimates for the three factor-specific segmentation indices and the aggregate index, at the monthly frequency. (The LASSO retained all regressors in all four regressions, so none are omitted, cf. Table 7.) Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2.

	MKT	SMB	HML	Aggregate
TED spr	-0.036 (0.059)	-0.171* (0.101)	-0.081 (0.113)	-0.096 (0.080)
T-bill	-0.069 (0.082)	-0.319* (0.139)	0.077 (0.148)	-0.103 (0.109)
Volume	0.397*** (0.094)	0.519** (0.167)	0.608*** (0.171)	0.508*** (0.129)
Fin uncert	-0.043 (0.083)	-0.063 (0.148)	-0.080 (0.154)	-0.062 (0.115)
PS illiq	0.085 (0.064)	0.231 (0.115)	0.139 (0.122)	0.152 (0.089)
Amihud	0.309*** (0.094)	0.469*** (0.157)	0.560*** (0.166)	0.446*** (0.124)
Recession	0.718 (0.408)	0.807 (0.703)	1.650* (0.728)	1.058* (0.555)
BM ratio	-0.038 (0.065)	-0.067 (0.114)	-0.119 (0.121)	-0.075 (0.089)
UP	-0.767** (0.290)	-1.694*** (0.485)	-1.258** (0.510)	-1.240*** (0.385)
VIX	-0.033 (0.050)	-0.172** (0.087)	-0.038 (0.096)	-0.081 (0.067)
Michigan sent	-0.024 (0.054)	-0.139 (0.091)	-0.053 (0.104)	-0.072 (0.073)
BW sent	0.118 (0.070)	0.320* (0.120)	0.102 (0.131)	0.180 (0.096)
R^2	0.285	0.310	0.228	0.333
p -value	0.001	0.001	0.001	0.001

Perhaps the most noticeable difference between the six-factor and three-factor regression analyses is for the value factor segmentation index: in the six-factor analysis the LASSO retained only Amihud illiquidity as a useful explanatory variable, while in the three-factor case all twelve regressors are retained.¹⁶ Overall, the three-factor analysis reinforces the main conclusions from the six-factor analysis: the most stable state relations remain tied to market-wide trading activity and Amihud illiquidity, with additional roles for market performance and recession conditions. Supplemental Figure S.1 presents the corresponding observed and fitted monthly segmentation indices under the three-factor specification.

Finally, the Hansen-Lunde persistence results provide a similar broad picture under the three-factor specification. Table S.11 in the supplemental appendix shows that the static persistence estimates range from 0.95 to 0.96. The main level/persistence distinctions also remain: higher trading volume is associated with significantly lower Aggregate persistence, Pastor-Stambaugh illiquidity with higher Aggregate persistence, while Amihud illiquidity has essentially no Aggregate persistence effect.

6 Conclusion

This paper proposes a new measure for the degree of integration/segmentation in the U.S. equity market. We gauge market segmentation by the degree to which compensation for systematic risk varies in the cross section. In an integrated market, investors earn the same premium for bearing risk regardless of the specific asset providing the exposure. In a market with a *constant* degree of segmentation, cross-sectional differences in risk prices can exist, but they do not vary over time. The first of these hypotheses is rejected using the test of Patton and Weller (2022). We test the second using a new bootstrap-based test and we

¹⁶This is likely because the factors omitted when using the three-factor model have explanatory power and are correlated with the included factors, and so the three-factor model factor loadings reflect not only the included factors but part of the excluded factors.

strongly reject the restriction. We find that for approximately one-fifth of our sample period, we cannot reject the null of a fully integrated market with equal prices of factor risk at the 10% significance level, while for nearly two-thirds of our sample we reject market integration at the 1% significance level. That is, the U.S. equity market is segmented and the degree of segmentation varies significantly over time.

We use an extension of k -means clustering to detect latent groups of test assets that generate different risk prices. In our collection of 234 sort portfolios, our cross-validation method estimates three clusters, which may be roughly labeled as “core market,” “small-cap core,” and “speculative periphery.” We construct a factor-specific index of time-varying segmentation using the cross-group differences in the risk premium associated with that factor in each period. A simple average of these across factors yields our “aggregate” segmentation index. We find that the improvement in Sharpe ratio from allowing for multiple clusters relative to a single cluster is significant when the segmentation index is high, but the corresponding gains are smaller and statistically insignificant otherwise.

We consider the channels that could lead to time-varying market segmentation through the lens of a stylized “preferred habitat” model. Equity investor clienteles generate relative factor risk imbalances across clusters/habitats, and arbitrageurs compress the resulting differences subject to basis risk and habitat-specific intermediation costs. The model allows us to consider how a set of macro-financial variables tracking market liquidity, funding liquidity, trading pressure, and market volatility can help explain time variation in market segmentation. At the monthly frequency, a collection of twelve such variables explains about 30% of the variation in market segmentation, indicating that some of the variation in market segmentation is attributable to known measures of market quality. We also find that the degree of market segmentation is highly persistent, after addressing the presence of measurement error, with an estimated first-order autocorrelation of 0.95 for the Aggregate segmentation

index. When we allow the persistence of market segmentation to vary with macro-financial variables, we find that the variables associated with the persistence of segmentation need not coincide with those associated with its contemporaneous level.

Looking across these state variables, the segmentation index is most strongly associated with measures of market illiquidity and trading conditions: correlations with the market illiquidity measures of [Amihud \(2002\)](#) and [Pastor and Stambaugh \(2003\)](#) are around 0.15-0.2, and elevated aggregate trading volume and NBER recessions are also associated with wider segmentation. In contrast, the level of the index is essentially uncorrelated with funding liquidity proxies such as the TED spread and the Treasury-bill rate. Viewed through the preferred-habitat model, the level results suggest that segmentation is driven primarily by the quantity of relative demand imbalances that intermediaries must absorb and by the cost of transacting across habitats. The persistence results provide a complementary role for funding conditions: higher TED spreads are associated with more persistent segmentation, suggesting that aggregate funding conditions may matter for how quickly existing pricing differences are compressed even when they are not strongly associated with their contemporaneous magnitude. We conclude that the law of one price of risk is not a fixed property of the U.S. equity market but a state-dependent outcome: it holds, approximately, when markets are liquid and order flow is easily absorbed, and it fails by economically meaningful margins when liquidity is scarce and trading pressure is high.

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Appendix

The appendix contains additional methodological and inferential details supporting the main analysis. Appendix A describes the bootstrap tests of market integration and constant market segmentation. Appendix B presents the effect-coded estimation of group deviations and the estimation-error adjustment. Appendix C describes Sharpe-ratio inference. Appendix D provides the preferred-habitat derivation, and Appendix E describes the estimation of time-varying autocorrelation in the presence of measurement error. Additional implementation details, group diagnostics, state-variable construction, and coefficient-level regression results are reported in the Supplemental Appendix.

A A bootstrap test of constant market segmentation

We consider two groups and define the estimated difference in risk prices across groups, and its covariance matrix, as :

$$\hat{c}_t = \hat{\lambda}_{1,t} - \hat{\lambda}_{2,t}, \quad V_t = \mathbb{V}[\hat{c}_t] \quad (18)$$

To test for time-invariant segmentation we use the test statistic:

$$\hat{R}_T = \frac{1}{T} \sum_{t=1}^T (\hat{c}_t - \bar{c}_T)^\top V_t^{-1} (\hat{c}_t - \bar{c}_T) \quad (19)$$

$$\text{where} \quad \bar{c}_T = \left(\sum_{t=1}^T V_t^{-1} \right)^{-1} \sum_{t=1}^T V_t^{-1} \hat{c}_t \quad (20)$$

The inverse-variance weights in equation (20) yield the estimate of constant segmentation, $\bar{c}_T$, that minimizes the test statistic in equation (19).

We obtain bootstrap draws of this statistic as follows. We first resample the sequence of dates using the stationary bootstrap (Politis and Romano, 1994), with an expected block length of 63 trading days. Let s_t^b denote the original date selected at position t in bootstrap sample b . We resample the entire cross-section jointly, including factor exposures, regression

weights, estimated risk prices, and regression residuals. We then apply the wild bootstrap (Liu, 1988) to the cross-sectional regression residuals to obtain returns satisfying the null hypothesis of constant segmentation:

$$r_{i,t}^b = \beta_{i,s_t^b}^\top \left(\lambda_{0,s_t^b} + (-1)^{1+\gamma_i} \bar{c}_T / 2 \right) + \xi_{i,t}^b e_{i,s_t^b}, \quad \xi_{i,t}^b \sim iid \text{ Rademacher}, \quad (21)$$

Recall $\gamma_i \in \{1, 2\}$ denotes portfolio i 's group assignment, so the term $(-1)^{1+\gamma_i} \bar{c}_T / 2$ assigns deviations $\bar{d}_{1,T} = \bar{c}_T / 2$ and $\bar{d}_{2,T} = -\bar{c}_T / 2$. Further recall that a Rademacher random variable takes the values ± 1 with equal probability. These multipliers preserve the squared residuals at the resampled observations, allowing for cross-sectional and time-series heteroskedasticity. Group assignments remain fixed throughout the procedure. For each bootstrap sample, we re-estimate the group risk prices and their covariance matrices, and use the resulting bootstrap covariance matrices to estimate $\tilde{c}_T^b$ and $\tilde{R}_T^b$ as in equations (19)-(20). We use $B = 9,999$ bootstrap samples and compute the p -value as

$$\hat{p} = \frac{1 + \sum_{b=1}^B \mathbf{1}\{\tilde{R}_T^b \geq \hat{R}_T\}}{B + 1}.$$

A bootstrap version of the “dynamic” test of market integration in Patton and Weller (2022) can be obtained by imposing a zero rather than an unrestricted constant difference in risk prices: set $\bar{c}_T = 0$ in the bootstrap-return equation (21) and in the observed statistic in equation (19). Then, for each bootstrap sample, re-estimate the group risk prices and covariance matrices as above but calculate the statistic relative to zero rather than subtracting the constant $\tilde{c}_T^b$. This tests whether segmentation is constant and equal to zero, rather than merely constant. When we implement this test we find the bootstrap p -value to be less than 0.001, consistent with the “dynamic” test p -value reported in Table 3.

B Effect-coded estimation of group deviations

Using the group assignments obtained in Section 3.2, we estimate the common and group-specific factor risk prices separately on each date. The dependent variable is the daily excess return, and the same rolling-window factor exposures and full-sample group assignments are used throughout.

We estimate the model using “effect coding.” For a given date t , let $y_t = (r_{1,t}^e, \dots, r_{N_t,t}^e)^\top$ denote the $N_t \times 1$ vector of excess returns and let B_t denote the $N_t \times K$ matrix whose i th row is $\widehat{\beta}_{i,t}^\top$. We write the cross-sectional model as

$$y_t = B_t \lambda_{0,t} + C_t \theta_t + u_t,$$

where C_t contains interactions between those factor exposures and the estimated group assignments. The interaction coefficients θ_t capture differences in factor risk premia across groups and the coefficient $\lambda_{0,t}$ captures the baseline factor risk premia. The differences in risk premia are constrained to sum to zero across groups as follows. Let

$$M_G = I_G - \frac{1}{G} \mathbf{1} \mathbf{1}^\top$$

denote the centering matrix, and let Q contain the eigenvectors corresponding to its $G - 1$ nonzero eigenvalues. We define

$$E = Q \sqrt{\frac{G}{G-1}}, \tag{22}$$

so that $E^\top \mathbf{1} = 0$. Effect coding therefore represents the G centered group deviations using only $G - 1$ free sets of coefficients. If θ_t denotes those coefficients, the corresponding group deviations are

$$\widehat{d}_t = (E \otimes I_K) \widehat{\theta}_t.$$

By construction, these deviations sum to zero across groups for every factor and date.

We estimate θ_t using the Frisch-Waugh-Lovell theorem (see, e.g., [Davidson and MacK-](#)

innon, 1993), which provides a convenient way to separate the common and group-specific components. After applying the precision weights $w_{i,t} = 1/\widehat{\sigma}_{i,t}$, we first remove the component explained by the common factor exposures B_t from both the returns and the group-interaction regressors. We then regress the remaining return variation on the remaining group-interaction variation. This yields $\widehat{\theta}_t$. Given these estimated group effects, we re-estimate the common risk-price vector from

$$\widehat{\lambda}_{0,t} = (B_t^\top W_t B_t)^{-1} B_t^\top W_t (y_t - C_t \widehat{\theta}_t), \quad (23)$$

where $W_t = \text{diag}(w_{1,t}^2, \dots, w_{N_t,t}^2)$. This final step ensures that the common and group-specific risk prices come from the same decomposition.

The date-specific regression also provides a heteroskedasticity-robust covariance matrix for $\widehat{\theta}_t$. Let X_t denote the weighted group-interaction regressors after the common factor exposures have been removed, and let $\widehat{\Omega}_t$ denote the diagonal matrix of squared residuals from the weighted cross-sectional regression. The covariance estimator is

$$\widehat{V}_{\theta,t} = (X_t^\top X_t)^{-1} X_t^\top \widehat{\Omega}_t X_t (X_t^\top X_t)^{-1}.$$

Mapping this covariance matrix into the space of group deviations gives

$$\widehat{V}_{d,t} = (E \otimes I_K) \widehat{V}_{\theta,t} (E \otimes I_K)^\top.$$

Although $\widehat{\Omega}_t$ is diagonal, $\widehat{V}_{d,t}$ generally is not: the G centered group deviations are functions of the same $G-1$ sets of estimated coefficients, which induces covariance across their estimation errors.

For factor k , let $\widehat{\Sigma}_{k,t}$ contain the G rows and columns of $\widehat{V}_{d,t}$ corresponding to that factor. This is the matrix that appears in the estimation-error adjustment in equation (7).

C Sharpe-ratio inference

Let SR_{Group} and SR_{Base} denote the Sharpe ratios of the portfolios constructed under group-specific and common factor risk prices, respectively. We test the one-sided null:

$$H_0 : \text{SR}_{\text{Group}} \leq \text{SR}_{\text{Base}} \quad \text{versus} \quad H_a : \text{SR}_{\text{Group}} > \text{SR}_{\text{Base}}. \quad (24)$$

All tests are based on portfolio returns observed on common dates within the relevant segmentation tercile. Annualization is used only for reporting the Sharpe ratios in Table 4.

Our primary inference procedure is the studentized time-series bootstrap of [Ledoit and Wolf \(2008\)](#). Let

$$\hat{\Delta} = \widehat{\text{SR}}_{\text{Group}} - \widehat{\text{SR}}_{\text{Base}} \quad (25)$$

denote the estimated difference in Sharpe ratios. This difference is a smooth function of the two sample means and two uncentered second moments. Its sampling variability is estimated using the delta method and the long-run covariance matrix of this moment vector, yielding the test statistic

$$t^{\text{obs}} = \frac{\hat{\Delta}}{\widehat{s}(\hat{\Delta})}. \quad (26)$$

We generate $M = 1,999$ bootstrap samples using a circular block bootstrap with a fixed block length of six months, resampling the two portfolio returns jointly so that their contemporaneous dependence is preserved. The block resampling also allows for time-series dependence within each return series. For bootstrap sample m , let $\hat{\Delta}^{*,m}$ denote the estimated Sharpe-ratio difference and let $\widehat{s}(\hat{\Delta}^{*,m})$ denote its estimated standard error. The centered studentized bootstrap statistic is

$$t_m^* = \frac{\hat{\Delta}^{*,m} - \hat{\Delta}}{\widehat{s}(\hat{\Delta}^{*,m})}. \quad (27)$$

The one-sided bootstrap p -value is then

$$\hat{p}^{\text{boot}} = \frac{1 + \sum_{m=1}^M \mathbf{1}\{t_m^* \geq t^{\text{obs}}\}}{M + 1}. \quad (28)$$

The long-run covariance matrix used to studentize the observed statistic is estimated using a [Newey and West \(1987\)](#) estimator with six monthly lags.

As a robustness check, we also compute the one-sided [Jobson and Korkie \(1981\)](#) test with the correction of [Mommel \(2003\)](#). This test relies on the classical *iid* Gaussian assumption, whereas the bootstrap procedure allows for more general distributional and time-series dependence. In our sample the Jobson–Korkie/Mommel test yields conclusions very similar to those from the [Ledoit and Wolf \(2008\)](#) bootstrap inference.

D Preferred-habitat derivation of the state regression

This appendix gives the derivation behind the economic channel in [Section 4.1](#).

Let the group-specific price of factor risk be

$$\lambda_{g,t} = \lambda_{0,t} + d_{g,t}, \quad \lambda_{0,t} = \frac{1}{G} \sum_{g=1}^G \lambda_{g,t}, \quad \frac{1}{G} \sum_{g=1}^G d_{g,t} = 0.$$

Let $c_{g,t}$ denote the signed per-unit intermediation cost in group g , and define

$$\bar{c}_t = \frac{1}{G} \sum_{g=1}^G c_{g,t}, \quad \tilde{c}_{g,t} = c_{g,t} - \bar{c}_t.$$

Arbitrageurs choose positions $x_{g,t}$ in the K -dimensional factor-risk exposure of each group. The positions are relative across groups, so they satisfy $\frac{1}{G} \sum_{g=1}^G x_{g,t} = 0$. Given the mean-variance risk aversion parameter γ and basis-risk covariance matrix Ω_t , the arbitrageur solves

$$\max_{\{x_{g,t}\}_{g=1}^G} \frac{1}{G} \sum_{g=1}^G \left[x_{g,t}^\top (\lambda_{0,t} + d_{g,t} - c_{g,t}) - \frac{\gamma}{2} x_{g,t}^\top \Omega_t x_{g,t} \right] \quad \text{subject to} \quad \frac{1}{G} \sum_{g=1}^G x_{g,t} = 0.$$

The Lagrangian is

$$\mathcal{L} = \frac{1}{G} \sum_{g=1}^G \left[x_{g,t}^\top (\lambda_{0,t} + d_{g,t} - c_{g,t}) - \frac{\gamma}{2} x_{g,t}^\top \Omega_t x_{g,t} \right] - \mu_t^\top \left(\frac{1}{G} \sum_{g=1}^G x_{g,t} \right),$$

where μ_t is a K -dimensional Lagrange multiplier. The first-order condition is

$$\lambda_{0,t} + d_{g,t} - c_{g,t} - \gamma \Omega_t x_{g,t} - \mu_t = 0.$$

Taking the equal-weighted average across groups and using

$$\frac{1}{G} \sum_{g=1}^G d_{g,t} = 0 \quad \text{and} \quad \frac{1}{G} \sum_{g=1}^G x_{g,t} = 0$$

gives $\mu_t = \lambda_{0,t} - \bar{c}_t$. Substituting this expression back into the first-order condition gives

$$d_{g,t} = \gamma \Omega_t x_{g,t} + (c_{g,t} - \bar{c}_t) = \gamma \Omega_t x_{g,t} + \tilde{c}_{g,t}.$$

Let $s_{g,t}$ denote the net factor-risk imbalance that arbitrageurs must absorb in group g . Define the relative imbalance

$$\bar{s}_t = \frac{1}{G} \sum_{g=1}^G s_{g,t}, \quad \tilde{s}_{g,t} = s_{g,t} - \bar{s}_t, \quad \frac{1}{G} \sum_{g=1}^G \tilde{s}_{g,t} = 0.$$

With the sign convention used in the main text, market clearing in relative exposures gives

$x_{g,t} = \tilde{s}_{g,t}$. Therefore the group-specific price-of-risk deviation is $d_{g,t} = \gamma \Omega_t \tilde{s}_{g,t} + \tilde{c}_{g,t}$.

It is worth noting that the factor-neutrality constraint does not make the relative trade riskless. Suppose the payoff to factor-risk exposure in group g can be written as

$$r_{g,t+1}^F = f_{t+1} + b_{g,t+1},$$

where f_{t+1} is the common factor payoff and $b_{g,t+1}$ is the group-specific basis payoff. The relative position eliminates the common factor payoff because

$$\left(\frac{1}{G} \sum_{g=1}^G x_{g,t} \right)^\top f_{t+1} = 0,$$

but the group-specific basis terms need not cancel. The matrix Ω_t should be interpreted as the covariance matrix of the unhedgeable basis risk in the relative cross-group trade. It does not create segmentation by itself; it affects segmentation through the riskiness of the relative position that arbitrageurs must hold.

For factor k , let e_k be the k th unit vector. The group-specific wedge for factor k is

$$d_{g,k,t} = e_k^\top d_{g,t} = \gamma e_k^\top \Omega_t \tilde{s}_{g,t} + \tilde{c}_{g,k,t}, \quad \tilde{c}_{g,k,t} = e_k^\top \tilde{c}_{g,t}.$$

The theoretical segmentation measure is

$$\sigma_{k,t} = \left[\frac{1}{G} \sum_{g=1}^G d_{g,k,t}^2 \right]^{1/2}.$$

Substituting the pricing relation gives

$$\sigma_{k,t}^2 = \frac{1}{G} \sum_{g=1}^G (\gamma e_k^\top \Omega_t \tilde{s}_{g,t} + \tilde{c}_{g,k,t})^2,$$

or equivalently

$$\sigma_{k,t}^2 = \gamma^2 \frac{1}{G} \sum_{g=1}^G (e_k^\top \Omega_t \tilde{s}_{g,t})^2 + \frac{1}{G} \sum_{g=1}^G \tilde{c}_{g,k,t}^2 + 2\gamma \frac{1}{G} \sum_{g=1}^G (e_k^\top \Omega_t \tilde{s}_{g,t}) \tilde{c}_{g,k,t}.$$

This decomposition shows why the empirical state variables are used as proxies rather than as structural primitives. Let

$$\mathcal{Q}_t = (\gamma, \Omega_t, \{\tilde{s}_{g,t}\}_{g=1}^G, \{\tilde{c}_{g,t}\}_{g=1}^G)$$

collect the latent primitives. The segmentation index is a nonlinear function of these primitives,

$$\sigma_{k,t} = \mathcal{S}_k(\mathcal{Q}_t).$$

If the observable state vector Z_t proxies for time variation in $\mathcal{Q}_t$, then a first-order projection gives the reduced-form state regression used in the main text:

$$\tilde{\sigma}_{k,t}^{adj} = a_k + b_k^\top Z_t + u_{k,t}.$$

The coefficients summarize how observable states covary with the equilibrium wedges. They should not be interpreted as separate estimates of demand imbalances, intermediation costs, risk-bearing capacity, or basis-risk primitives.

E Time-varying autocorrelation of a time series measured with error

Our estimate of the constant autocorrelation of the segmentation indices is based on Theorem 3 of [Hansen and Lunde \(2014\)](#), henceforth HL. This appendix describes the extension to allow the first-order autocorrelation coefficient to vary with a vector of covariates by exploiting the method's interpretation as a form of GMM. Let

$$\begin{aligned} x_t &= y_t + \eta_t \\ y_t &= c + \rho_t y_{t-1} + \varepsilon_t \\ \rho_t &= \bar{\rho} + \gamma^\top z_{t-1} \end{aligned} \tag{29}$$

where x_t is the observed proxy for the latent process of interest, y_t , and $z_{t-1} \in \mathbb{R}^k$ is a vector of mean-zero covariates measured without error. Letting $\mathcal{F}_t$ denote the information generated by $\{[x_s, z_s], s \leq t\}$, we assume $\mathbb{E}[\varepsilon_t \mid \mathcal{F}_{t-1}] = \mathbb{E}[\eta_t \mid \mathcal{F}_{t-1}, z_t] = 0$.

Combining the equations above yields a regression in observables:

$$x_{t+1} = c + \bar{\rho} x_t + \gamma^\top (z_t x_t) + u_{t+1}, \quad (30)$$

$$\text{where } u_{t+1} = \varepsilon_{t+1} + \eta_{t+1} - (\bar{\rho} + \gamma^\top z_t) \eta_t,$$

This is the time-varying analog of HL's Lemma 1. Because u_{t+1} contains η_t , OLS applied to equation (30) is inconsistent (as noted by HL's Theorem 1 for the constant case). Under the assumptions above, $\mathbb{E}[u_{t+1} \mid \mathcal{F}_{t-1}, z_t] = 0$, so lagged observations and their interactions with z_t remain valid instruments.

Let $\theta = (c, \bar{\rho}, \gamma^\top)^\top \in \mathbb{R}^{2+k}$ and $W_t = (1, x_t, z_t^\top x_t)^\top$. The instrument vector stacks demeaned lags and their interactions with the covariates,

$$S_t = \left(1, \{x_{t-j} - \bar{x}_j\}_{j=j_1}^J, \{z_{m,t} (x_{t-j} - \bar{x}_j)\}_{m=1, \dots, k}^{j=j_1, \dots, J} \right)^\top \in \mathbb{R}^{1+(k+1)q}, \quad q = J - j_1 + 1, \quad (31)$$

where (j_1, J) are the first and last lags used in the set of instruments. The model then implies the unconditional moment conditions:

$$\mathbb{E}[S_t (x_{t+1} - W_t^\top \theta)] = 0. \quad (32)$$

We estimate θ using efficient GMM; see [Hall \(2004\)](#) for details.

Time-Varying U.S. Equity Market Integration

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This supplemental appendix provides additional implementation details, descriptive diagnostics, and estimation results. Section [S.1](#) describes the estimated latent pricing groups. Section [S.2](#) documents the construction of the macro-financial state variables. Section [S.3](#) reports daily correlations between the aggregate segmentation index and selected state variables. Section [S.4](#) reports the additional coefficient-level results for the baseline six-factor specification, and Section [S.5](#) reports the corresponding regression and persistence results under the three-factor robustness specification.

S.1 Description of the estimated latent pricing groups

This section provides descriptive information on the full-sample latent pricing groups. The statistics and portfolio labels are used only to characterize the groups after estimation; they are not inputs to the grouping procedure, the selection of the number of groups, or the construction of the segmentation index.

Size is the clearest, but not the only, organizing dimension. Group 2 contains all 25 portfolios in the smallest size row of the five-by-five sorts. Group 3 contains 23 of the 25 portfolios in the second-smallest size row and has the highest average six-factor R^2 and lowest residual variance. Group 1 is the largest group, contains most portfolios in the middle size rows, and includes 32 of the 49 industry portfolios. The largest size row and the extremes of the characteristic sorts are distributed across all three groups, confirming that the partition is not a one-dimensional size classification. Group 2 has the highest

Table S.1: **Latent groups by original portfolio family.** The table cross-tabulates the estimated full-sample group assignments with the original portfolio families.

Portfolio family	Group 1	Group 2	Group 3
Size	5	3	2
Book-to-market	2	5	3
Momentum	4	3	3
STR	4	2	4
Investment	2	4	4
Operating profitability	1	6	3
Size-book-to-market	10	8	7
Size-momentum	9	8	8
Size-STR	13	6	6
Size-investment	10	7	8
Size-operating profitability	10	8	7
Industry	32	11	6
Total	102	71	61

average residual variance and kurtosis, but differences in the remaining return and factor characteristics are comparatively modest.

Table S.1 reports counts by original portfolio family, Table S.2 reports the one-way characteristic sorts, Table S.3 reports the industry assignments, Table S.4 reports the five-by-five size-characteristic assignments, and Table S.5 summarizes return and factor characteristics.

Table S.2: **Group assignments for one-way sorted portfolios.** Each entry reports the estimated latent group for the corresponding one-way sorted Kenneth French portfolio.

Characteristic	<i>Decile</i>									
	<i>Low</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>High</i>
Size	2	2	3	3	1	1	1	1	1	2
Book-to-market	2	3	1	2	2	2	2	1	3	3
Momentum	2	2	1	1	3	2	1	1	3	3
Short-term reversal	1	1	1	1	2	2	3	3	3	3
Investment	2	3	1	3	2	2	3	3	2	1
Operating profitability	3	1	2	2	2	2	3	3	2	2

Table S.3: **Industry portfolios by latent group.** The table lists the 49 Kenneth French industry portfolios by estimated latent group.

Group	Industry portfolios
1	Food, Soda, Smoke, Toys, Fun, Books, Hshld, Clths, MedEq, Chems, Rubbr, Txtls, BldMt, Cnstr, Steel, FabPr, Mach, Aero, Ships, Mines, Util, PerSv, BusSv, LabEq, Paper, Boxes, Trans, Whlsl, Rtail, Meals, REst, Hlth
2	Autos, Gold, Coal, Oil, Telcm, Hardw, Chips, Banks, Insur, Fin, Softw
3	Agric, Beer, Drugs, ElcEq, Guns, Other

Table S.4: **Group assignments for 5-by-5 size-characteristic portfolios.** Each entry reports the estimated latent group for the corresponding Kenneth French 5-by-5 portfolio. Rows are size quintiles and columns are quintiles of the second sorting variable.

Portfolio family	Size	Char1	Char2	Char3	Char4	Char5
Size-book-to-market	ME1	2	2	2	2	2
	ME2	3	3	3	3	3
	ME3	1	1	1	1	3
	ME4	1	1	1	1	1
	ME5	2	2	2	1	3
Size-momentum	ME1	2	2	2	2	2
	ME2	1	3	3	3	3
	ME3	3	1	1	1	3
	ME4	2	1	1	1	3
	ME5	2	1	2	1	3
Size-short-term reversal	ME1	2	2	2	2	2
	ME2	1	3	3	3	3
	ME3	1	1	1	1	1
	ME4	1	1	1	1	1
	ME5	1	1	2	3	3
Size-investment	ME1	2	2	2	2	2
	ME2	3	3	3	3	3
	ME3	1	1	1	1	1
	ME4	1	1	1	1	1
	ME5	3	3	2	3	2
Size-operating profitability	ME1	2	2	2	2	2
	ME2	3	3	3	3	3
	ME3	3	1	1	1	1
	ME4	1	1	1	1	1
	ME5	1	2	2	3	2

Table S.5: **Return and factor characteristics by latent group.** The table reports equal-weighted averages of portfolio-level characteristics within each estimated group. Mean, variance, skewness, and kurtosis are computed from daily portfolio returns. The factor diagnostics are from six-factor regressions using MKT, SMB, HML, MOM, RMW, and CMA.

	Group 1	Group 2	Group 3
Mean	0.051	0.048	0.048
Var.	1.493	1.558	1.429
Skew.	-0.342	-0.311	-0.381
Kurt.	13.887	15.601	12.125
FF6 (R^2)	0.809	0.849	0.870
Resid. var.	0.328	0.356	0.202
MKT	1.024	0.986	1.024
SMB	0.357	0.387	0.445
HML	0.104	0.104	0.112
MOM	-0.054	-0.074	0.007
RMW	0.063	-0.005	0.009
CMA	0.043	0.024	0.050

S.2 State-variable construction

Most of the macro-financial state variables are standard series used without additional construction beyond the transformations reported in Table 2, but some variables require further explanation. We obtain the TED spread from FRED through to its final available observation and extend it thereafter using SOFR minus the three-month Treasury bill rate. Aggregate S&P 500 trading volume is constructed from CRSP as the sum of absolute price times trading volume across S&P 500 constituents on each date and is stochastically detrended by dividing by its backward-looking mean over 504 trading days. The S&P 500 Amihud measure is the absolute S&P 500 return divided by aggregate S&P 500 dollar volume and is similarly normalized by its backward-looking 504-trading-day mean. For Pastor-Stambaugh liquidity (available at <https://finance.wharton.upenn.edu/~stambaug/>), we use the non-traded

aggregate liquidity series and reverse its sign so that larger values indicate greater illiquidity. The VIX series uses the CBOE VIX where available and is augmented prior to 1990 using a realized-volatility-based proxy. Specifically, we compute the annualized standard deviation of daily S&P 500 returns over a trailing 21-trading-day window and regress the observed VIX on this realized-volatility measure over their overlapping sample. We use the fitted relation to construct the pre-1990 VIX proxy.

S.3 Daily correlations with state variables

Table S.6: **Daily correlation between segmentation and selected state variables.** This table reports correlations among the daily aggregate segmentation index described in Section 3.3 and a subset of the variables described in Section 4.2. The Pastor–Stambaugh series is sign-flipped so that higher values indicate greater market illiquidity. The sample contains 9,346 daily observations from January 3, 1986 to December 31, 2024.

	Dispersion	Amihud	P&S	Volume	VIX	TED
Amihud illiquidity	0.17					
P&S illiquidity	0.12	0.10				
Trading volume	0.20	0.04	0.02			
VIX	0.03	0.17	-0.02	0.09		
TED spread	0.02	0.03	0.00	0.06	0.06	
T-bill rate	-0.07	-0.04	-0.02	-0.10	-0.06	-0.70

S.4 Regression coefficients for the six-factor model

This section reports the regression coefficients underlying the baseline joint state-dependence tests in Table 6. Tables S.7 and S.8 report the OLS estimates based on daily and monthly segmentation indices, while Table S.9 reports the post-LASSO OLS estimates for the daily indices. The monthly post-LASSO estimates are reported in Table 7 in the main text. Each table includes the six factor-specific segmentation indices and the Aggregate.

Table S.7: **OLS regression results, daily indices.** This table reports OLS parameter estimates for the six factor-specific segmentation indices and the aggregate index, at the daily frequency. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2 of the main paper.

	MKT	SMB	HML	MOM	RMW	CMA	Agg.
TED spr	0.026 (0.026)	-0.092 (0.059)	-0.082 (0.068)	-0.041 (0.077)	-0.013 (0.065)	-0.079 (0.054)	-0.047 (0.035)
T-bill	0.012 (0.029)	-0.105 (0.063)	-0.054 (0.073)	-0.085 (0.081)	-0.096 (0.070)	-0.138* (0.058)	-0.078 (0.040)
Volume	0.297*** (0.048)	0.516*** (0.102)	0.571*** (0.123)	0.668*** (0.103)	0.709*** (0.106)	0.421*** (0.079)	0.530*** (0.079)
Fin uncert	-0.029 (0.053)	-0.069 (0.115)	-0.125 (0.134)	0.080 (0.118)	-0.171 (0.123)	-0.055 (0.092)	-0.061 (0.090)
PS illiq	0.061 (0.034)	0.238*** (0.074)	0.237** (0.087)	0.168** (0.083)	0.213** (0.078)	0.131** (0.060)	0.175*** (0.054)
Amihud	0.130*** (0.029)	0.206*** (0.063)	0.196** (0.072)	0.418*** (0.071)	0.199** (0.068)	0.229*** (0.052)	0.230*** (0.045)
Recession	0.480* (0.248)	1.721** (0.542)	1.661* (0.652)	2.208*** (0.514)	1.534*** (0.570)	0.728* (0.405)	1.389** (0.421)
BM ratio	0.057** (0.035)	0.123** (0.077)	0.227** (0.087)	0.135* (0.083)	0.093 (0.079)	0.106* (0.061)	0.123*** (0.055)
UP	-0.554** (0.205)	-1.342*** (0.435)	-1.539** (0.535)	-0.545* (0.414)	-0.188 (0.456)	0.055 (0.327)	-0.685** (0.349)
VIX	-0.005 (0.019)	-0.013 (0.038)	-0.045 (0.044)	-0.112 (0.054)	-0.041 (0.042)	0.047 (0.037)	-0.028 (0.021)
Mich sent	-0.043 (0.032)	-0.072 (0.070)	-0.004 (0.078)	-0.085 (0.080)	-0.121* (0.073)	-0.050 (0.061)	-0.062 (0.050)
BW sent	0.014 (0.041)	0.171 (0.090)	-0.045 (0.103)	0.088 (0.095)	0.144 (0.092)	0.066 (0.070)	0.073 (0.067)
R^2	0.054	0.068	0.053	0.046	0.047	0.029	0.130
p -value	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Table S.8: **OLS regression results, monthly indices.** This table reports OLS parameter estimates for the six factor-specific segmentation indices and the aggregate index, at the monthly frequency. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2 of the main paper.

	MKT	SMB	HML	MOM	RMW	CMA	Agg.
TED spr	-0.016 (0.052)	-0.166* (0.104)	-0.212* (0.130)	-0.236 (0.128)	-0.173 (0.122)	-0.035 (0.099)	-0.140* (0.082)
T-bill	-0.112 (0.070)	-0.298 (0.142)	-0.071 (0.182)	-0.107 (0.156)	-0.123 (0.162)	-0.232 (0.121)	-0.157 (0.114)
Volume	0.259** (0.082)	0.485** (0.173)	0.528* (0.214)	0.559*** (0.172)	0.828*** (0.185)	0.240 (0.135)	0.483*** (0.135)
Fin uncert	-0.074 (0.072)	-0.083 (0.154)	-0.178 (0.183)	0.078 (0.168)	-0.244 (0.171)	-0.126 (0.127)	-0.105 (0.122)
PS illiq	0.001 (0.058)	0.172 (0.119)	0.255 (0.147)	0.092 (0.142)	0.115 (0.133)	0.167 (0.103)	0.134 (0.095)
Amihud	0.283*** (0.082)	0.439*** (0.167)	0.529** (0.202)	0.743*** (0.181)	0.541*** (0.177)	0.401*** (0.142)	0.490*** (0.132)
Recession	0.226 (0.360)	1.354 (0.742)	1.487 (0.919)	2.281*** (0.744)	1.389* (0.803)	0.655 (0.576)	1.232* (0.592)
BM ratio	-0.002 (0.057)	-0.073 (0.113)	-0.037 (0.136)	0.016 (0.141)	-0.067 (0.132)	-0.146 (0.105)	-0.051 (0.092)
UP	-0.655** (0.250)	-1.614*** (0.506)	-2.185** (0.650)	-0.320 (0.536)	-0.530 (0.578)	0.235 (0.412)	-0.845** (0.415)
VIX	-0.023 (0.044)	-0.234*** (0.089)	0.033 (0.108)	-0.192* (0.111)	-0.155* (0.100)	0.059 (0.085)	-0.085* (0.067)
Mich sent	-0.036 (0.047)	-0.086 (0.091)	-0.052 (0.117)	-0.011 (0.122)	-0.139 (0.109)	-0.051 (0.087)	-0.062 (0.074)
BW sent	0.080 (0.060)	0.373* (0.125)	0.057 (0.151)	0.108 (0.144)	0.330 (0.138)	0.211 (0.105)	0.193 (0.100)
R^2	0.207	0.300	0.237	0.263	0.223	0.139	0.307
p -value	0.004	0.001	0.002	0.001	0.001	0.003	0.001

Table S.9: **Post-LASSO regression results, daily indices.** This table reports OLS estimates after LASSO variable selection for the six factor-specific segmentation indices and the aggregate index, at the daily frequency. An empty cell indicates that the variable was not selected. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2 of the main paper.

	MKT	SMB	HML	MOM	RMW	CMA	Agg.
TED spr	0.026 (0.026)	-0.092 (0.059)					
T-bill	0.012 (0.029)	-0.105 (0.063)		-0.057 (0.054)	-0.087 (0.046)	-0.097** (0.040)	-0.045 (0.024)
Volume	0.297*** (0.048)	0.516*** (0.102)		0.669*** (0.103)	0.709*** (0.106)	0.411*** (0.081)	0.531*** (0.079)
Fin uncert	-0.029 (0.053)	-0.069 (0.115)		0.080 (0.118)	-0.171 (0.123)		-0.062 (0.090)
PS illiq	0.061 (0.034)	0.238*** (0.074)		0.168** (0.083)	0.213** (0.078)	0.131** (0.060)	0.175*** (0.054)
Amihud	0.130*** (0.029)	0.206*** (0.063)		0.418*** (0.071)	0.199** (0.068)	0.263*** (0.054)	0.229*** (0.045)
Recession	0.480* (0.248)	1.721** (0.542)		2.216*** (0.515)	1.536*** (0.571)		1.398** (0.422)
BM ratio	0.057** (0.035)	0.123** (0.077)		0.135* (0.083)	0.093 (0.079)	0.116* (0.060)	0.124*** (0.055)
UP	-0.554** (0.205)	-1.342*** (0.435)		-0.546* (0.414)	-0.188 (0.456)		-0.686** (0.349)
VIX	-0.005 (0.019)	-0.013 (0.038)		-0.113 (0.054)	-0.041 (0.042)		-0.029 (0.021)
Mich sent	-0.043 (0.032)	-0.072 (0.070)		-0.085 (0.080)	-0.121* (0.073)	-0.051 (0.060)	-0.063 (0.050)
BW sent	0.014 (0.041)	0.171 (0.090)		0.088 (0.095)	0.144 (0.092)		0.074 (0.067)
R^2	0.054	0.068	0.000	0.046	0.047	0.026	0.129
p -value	0.001	0.001		0.001	0.001	0.001	0.001

S.5 Three-factor regression and persistence results

This section reports additional regression and persistence results for the three-factor specification. At the daily frequency, as at the monthly frequency discussed in the main text, LASSO retains all regressors for each factor-specific index and the aggregate index. The daily post-LASSO estimates therefore coincide with the OLS estimates reported below. We also report the persistence estimates and the observed and fitted monthly segmentation indices.

Table S.10: **OLS regression results, three-factor daily indices.** This table reports OLS parameter estimates for the three factor-specific segmentation indices and the aggregate index, at the daily frequency. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard deviation estimates from the stationary bootstrap. Stars are based on empirical two-sided p -values obtained by comparing the absolute observed HAC t -statistic with the placebo distribution of absolute HAC t -statistics. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The final row reports the p -value for the joint test that all slope coefficients are zero. An intercept (not reported) is included in all specifications. The regressors are described in Table 2 of the main paper.

	MKT	SMB	HML	Aggregate
TED spr	0.025 (0.030)	-0.022 (0.059)	-0.017 (0.061)	-0.005 (0.037)
T-bill	0.039 (0.033)	-0.088 (0.062)	0.002 (0.066)	-0.016 (0.041)
Volume	0.394*** (0.056)	0.547*** (0.095)	0.658*** (0.100)	0.533*** (0.074)
Fin uncert	-0.008 (0.064)	-0.048 (0.106)	-0.091 (0.113)	-0.049 (0.083)
PS illiq	0.123*** (0.039)	0.246*** (0.070)	0.214*** (0.076)	0.194*** (0.053)
Amihud	0.183*** (0.035)	0.147** (0.060)	0.303*** (0.063)	0.211*** (0.044)
Recession	0.862** (0.300)	1.331** (0.491)	1.782** (0.523)	1.325** (0.387)
BM ratio	0.051 (0.041)	0.104* (0.072)	0.093 (0.075)	0.083* (0.053)
UP	-0.580** (0.248)	-1.514*** (0.397)	-0.953** (0.432)	-1.015*** (0.327)
VIX	-0.020 (0.020)	0.031 (0.039)	-0.027 (0.042)	-0.005 (0.023)
Mich sent	-0.021 (0.038)	-0.110 (0.068)	-0.036 (0.071)	-0.055 (0.049)
BW sent	0.014 (0.048)	0.120 (0.084)	0.101 (0.087)	0.078 (0.064)
R^2	0.080	0.061	0.055	0.119
p -value	0.001	0.001	0.001	0.001

Table S.11: **Persistence of segmentation indices, three-factor model.** The first row of this table reports the [Hansen and Lunde \(2014\)](#) estimate of the first-order autocorrelation of each segmentation index (across the columns) using lags 2-8 as instruments. The remaining rows of the table present the coefficients when the autocorrelation coefficient is assumed to vary with the state variable given in the row, as described in Appendix E. Each state variable is considered separately. Continuous state variables are standardized while indicator variables remain in zero-one units. Parentheses contain standard errors. Significance at the 10%, 5% or 1% level is indicated with 1, 2, or 3 stars. The first row uses the full monthly sample period from January 1986 to December 2024, while the sample for the remaining rows starts in January 1986.

	MKT	SMB	HML	Aggregate
$\bar{\rho}$	0.961 (0.012)	0.959 (0.012)	0.951 (0.014)	0.957 (0.013)
TED spr	-0.017 (0.030)	-0.007 (0.015)	-0.024 (0.018)	-0.001 (0.015)
T-bill	-0.112 (0.084)	0.001 (0.019)	0.022 (0.021)	-0.010 (0.028)
Volume	0.082** (0.035)	-0.011 (0.022)	-0.124*** (0.032)	-0.137*** (0.036)
Fin uncert	-0.013 (0.015)	0.015 (0.015)	0.016 (0.013)	-0.012 (0.010)
PS illiq	0.045** (0.019)	0.061*** (0.016)	0.117*** (0.029)	0.045*** (0.017)
Amihud	0.016 (0.036)	0.014 (0.019)	0.028* (0.016)	0.005 (0.015)
Recession	-0.069** (0.028)	-0.454*** (0.145)	-0.153*** (0.044)	-0.074*** (0.028)
BM ratio	-0.066* (0.036)	0.104*** (0.024)	0.001 (0.033)	0.118*** (0.033)
UP	0.034 (0.037)	-0.065*** (0.025)	0.103** (0.044)	0.056** (0.027)
VIX	0.032 (0.046)	0.202*** (0.050)	0.110* (0.057)	0.079 (0.049)
Mich sent	0.109*** (0.037)	-0.113** (0.051)	0.116*** (0.039)	0.087*** (0.032)
BW sent	-0.021* (0.012)	-0.021 (0.017)	-0.017 (0.020)	-0.016* (0.009)

Figure S.1: **Observed and fitted segmentation indices, three-factor model.** The figure reports the observed monthly segmentation index and the fitted value from the OLS regression for each of the three factors and the aggregate index. All series are expressed in annualized two-standard-deviation spread units, measured in percentage points. Shaded regions denote NBER recessions. The sample period is January 1986 through December 2024.

