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Investor crowding ☆

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ABSTRACT

Asset pricing research provides evidence on the cross-section of asset prices, while it is relatively silent on the potential consequences of the pricing models' postulated differences in expected returns. At the same time, return differences may also result from investor behavior that is characterized by focus of attention on asset subclasses, sectors or even single issues, a phenomenon which we denote as "investor crowding". Realized return differences affect weights and may induce crowding in asset portfolios. We argue that crowding can be costly to investors as it affects the risk-return efficiency of market proxies, potentially causing a negative externality for passive investors. The absence of crowding in a long-run equilibrium can be characterized by a weights martingale condition, which imposes restrictions on risk premia dynamics. As such, static cross-sectional premia are difficult to reconcile with long-run absence of crowding. Suggesting an entropy-based measure of investor crowding, we study observed crowding behavior for the U.S. equity market. Our empirical results reveal that episodes of intense investor crowding are recurrent and that the relation with uncertainty is state-dependent. Uncertainty increases moderate crowding levels, i.e. investors tend to crowd when they are fearful. However, once crowding levels become elevated, uncertainty induces rebalancing away from dominant positions.

Speculative asset markets are subject to human asset pricing behavior that induces price changes in response to various pricing determinants. Financial research accordingly offers a vast related body of evidence on the cross-section of asset prices. However, one aspect has not yet attracted much interest in the literature and that is the question of return differences in the cross-section of asset prices. While the well-known Sharpe–Lintner–Mossin Capital Asset Pricing Model (CAPM) and its various popular extensions predict differing expected returns in the cross-section of returns, we are relatively unaware of the potential consequences and the long-run effects of such assumed static return differences. At the same time, considering common stock markets as most prominent examples, we know of repeated episodes during which investors' equity portfolios tend to become concentrated in relatively few

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holdings and then revert to more diversified states.[1] The present paper offers more insight into return differences and their relation to the latter behavior that can be summarized as investor crowding.[2]

We propose investor crowding as a relevant topic in the study of asset prices and financial decision making. When active institutional and active individual equity market investors tend to overweight subsets of the overall market universe, their investment and capital flows concentrate. This behavior is what one may define as crowding. Given market participants' investment actions, some active managers tend to concentrate their attention on *identical* asset subsets.[3] Focus of attention and associated investment flows yield significant differences in the cross-section of past observed returns. This cross-sectional return heterogeneity between favored and remainder stocks yields portfolios – including market portfolio proxies – whose weights can be relatively concentrated on relatively few holdings.

We argue that investor crowding has important implications for the efficiency of the vast equity market investments of institutional and individual investors worldwide. When investor crowding becomes prevalent – even if being apparently justified fundamentally – the degree of portfolio diversification will be reduced. Lack of diversification as a result of the decisions of active market participants thereby not only affects those active investors, but all investors in that market. In other words, crowding of active investors has an external effect on passive investors. More precisely, not only purely passive investors will be affected, but as shown in Wagner (2002), all regret-averse investors that choose their portfolios not only based on risk and expected return, but also based on expected regret due to possible deviations from the market benchmark. Hence, crowding causes investors who add new money to "follow the (active) crowd" and to suffer from a negative externality, thereby investing in a market portfolio proxy that potentially is far from efficient.

Besides considering static mean–variance efficiency, it is to be noted that lack of diversification is costly also in the dynamic setting. Using median terminal wealth as the relevant robust benchmark, Stutzer (2010) shows that diversifying of a typical passive index investment with – even negatively yielding – low risk bonds results in vastly improved results under regular rebalancing. When we target logarithmic terminal wealth as an alternative, well-known results from the lognormal distribution show that its expectation will relate to drift minus one-half of the return variance. Both of these dynamic perspectives hence underline that excess variance due to lack of diversification will cause adverse wealth effects in the long run. As a consequence, investors' expected returns will be too low for the levels of risk incurred.

In Section 1, we study portfolio weight dynamics in a discrete time setting with continuous compounding and Gaussian returns. We introduce a martingale condition for portfolio weights. This condition illustrates that individual asset return characteristics will affect cross-sectional return heterogeneity, future portfolio weights and hence relate to investor crowding.[4] Based on their long-run portfolio weight dynamics under the martingale condition, individual assets can be labeled either as "surviving", "dominating" or "threatened by extinction". It follows that static risk-premia are at odds with balanced market portfolios in the long run. In other words, we argue that observing relatively balanced market portfolio proxies is inconsistent with the literature's current dominant view on equity risk premia. However, it may be consistent with time-varying equity risk-premia,[5] which follow a stationary mean reverting process. This is because only then are long-term returns and resulting weight differences balanced. In order to study the phenomenon empirically, we suggest a novel measure of investor crowding. It measures portfolio weight concentration based on an entropy difference that is derived from portfolio weights.

In Section 2, we empirically study investor crowding for the U.S. stock market. We apply our entropy-based crowding measure for a sample of Standard and Poor's 500 index (S&P 500) constituents from 1990 to 2024. Our findings show that monthly crowding follows a cyclical pattern with recurring periods of high crowding alternating with periods of lower crowding tendency. Relying on our measure, we detect distinct crowding episodes including the Dot Com Bubble, the FAANG boom and the rise of the "Magnificent Seven". Our findings reveal that crowding is closely linked to shocks in financial uncertainty. The impact of uncertainty on crowding is state-dependent: in periods of moderate index concentration, uncertainty shocks amplify crowding as investors shift capital to a narrower set of market leaders. By contrast, once concentration is high, uncertainty shocks induce rebalancing away from dominant asset subclasses, sectors or single issues, reducing crowding rather than reinforcing it. Finally, our work ends with a brief conclusion in Section 3.

[1] In the U.S. stock market, we refer for example to the so-called "Nifty Fifty" during the 1960s and 1970s, to the "Dot Com Bubble" between 1995 and 2000 or to the more recent, initially called "FAANG" (Facebook, Amazon, Apple, Netflix and Google), later called "Magnificent Seven" phenomenon, which started around 2015. Further anecdotal evidence also indicates high levels of concentration in the market averages during the run-up to the crash of 1929.

[2] Only a few academic authors so far have used the term "crowding", but with a different perspective. Pedersen (2009) defines "crowded trades" as positions where many investors hold the same security. Stein (2009) argues that when many market participants engage in the same trade, they can drive prices away from fundamental value. See also Menkveld (2017) and Brown et al. (2022) who examine similarities in investors' trades and risk implications.

[3] Focus on asset subsets and investor attention can be traced back to Merton (1987). He suggests a static CAPM in which active investors focus their attention to subsets of the overall asset universe. Thereby, holdings of individual stocks tend to be concentrated, idiosyncratic volatility is priced in equilibrium, the market portfolio is *not* mean–variance efficient and assets with higher (lower) investor attention obtain higher (lower) price valuations with correspondingly lower (higher) expected returns. In a recent paper, Kwan et al. (2026) link institutional investor attention to portfolio allocation and future returns.

[4] Note that our concept of investor crowding is fundamentally different from the established concept of investor herding, where the common measurement approach follows the Christie and Huang (1995) cross-sectional standard deviation measure or the Chang et al. (2000) cross-sectional absolute deviation measure. Christie and Huang study herding and market stress. They consider cross-sectional return deviations (or idiosyncratic risk) as an indication of investors pricing assets in uniform fashion. When individual returns "herd around the market consensus", dispersions are predicted to be relatively low. Hence, while the *herding* concept is related to observed cross-sectional *return volatility homogeneity* – in contrast – our concept of *crowding* derives from cross-sectional *return heterogeneity*.

[5] Time-varying equity risk-premia can result within the Merton (1973) intertemporal CAPM when dynamic risk factor levels and asset exposures yield increased (decreased) market risk that drives market price levels down (up) and expected market returns up (down). In this line, Greenwood and Shleifer (2014) argue that when expectations of returns (and correlated past returns and flows) are high, future market returns are on average low, and this is as returns are equilibrium quantities.

1. Portfolio weights and investor crowding

We consider portfolio weights in a straightforward discrete time setting with continuous compounding and Gaussian returns. The starting point is an investable risky asset universe $\mathcal{U}$ with $|\mathcal{U}| = N$ and individual investable assets $i = 1, \dots, N$. Time is measured at discrete points, $t \in \theta = \{1, \dots\}$. Time-$t$ asset prices are given by $P_{i,t}$ and follow the continuous compounding model with log-returns $R_{i,t}$ and asset growth $P_{i,t} = P_{i,t-1} \exp\left(R_{i,t}\right)$. For convenience, we assume that the log-returns are approximately normal,

$$R_{i,t} \sim \mathcal{N}(\mu_i, \sigma_i^2),$$

with positive definite variance–covariance matrix, $\Omega = (\sigma_{i,j})_{N\times N}$, $\forall i, j$. The individual return series, $\{R_{i,t}\}_{t\in\theta}$, are then stochastic processes with independent and identically normally distributed components and σ-algebras denoted by $\mathcal{F}_{i,t}$.

A portfolio P defined on the universe $\mathcal{U}$ is given by fixed time-t individual asset holdings $n_{i,t} \geq 0$ under positive net supply. The value P_t of the portfolio is,

$$P_t = \sum_{i\in\mathcal{U}} n_{i,t} P_{i,t},$$

and its time-t capitalization weights $W_{i,t} \in [0; 1]$ are defined by:

$$W_{i,t} = n_{i,t}\, P_{i,t} \,/\, P_t, \text{ with: } \sum_{i\in\mathcal{U}} W_{i,t} = 1. \tag{1}$$

Given the normality of the individual log-returns, the portfolio log-return will be given by a sum of weighted dependent lognormal random variables. For reasons of tractability, we assume in the following that the number of individual investable assets N is large and that the portfolio log-return approximately obeys normality, i.e.:

$$R_{P,t} \sim \mathcal{N}(\mu_P, \sigma_P^2).$$

1.1. Individual portfolio weight dynamics

Given the above setting and the assumption that the portfolio P is self-financing, we are interested in the resulting dynamics of the time-$(t-1)$ to time-t portfolio weights in Eq. (1). Time-t portfolio weights are,

$$W_{i,t} = \frac{n_{i,t-1}\, P_{i,t-1} \exp\left(R_{i,t}\right)}{\sum_{j\in\mathcal{U}} n_{j,t-1}\, P_{j,t-1} \exp\left(R_{j,t}\right)} = W_{i,t-1} \frac{\exp\left(R_{i,t}\right)}{\sum_{j\in\mathcal{U}} W_{j,t-1} \exp\left(R_{j,t}\right)}, \tag{2}$$

where the final equation follows under multiplication with $1/P_{t-1}$. The above result for time-t portfolio weights can alternatively be expressed in terms of the portfolio return $R_{P,t}$ which then yields,

$$W_{i,t} = \frac{n_{i,t-1}\, P_{i,t-1} \exp\left(R_{i,t}\right)}{P_{t-1} \exp\left(R_{P,t}\right)} = W_{i,t-1} \exp\left(R_{i,t} - R_{P,t}\right) = W_{i,t-1} \exp\left(R_{\Delta,t}\right) \tag{3}$$

with the return differential denoted as $R_{\Delta,t} \equiv R_{i,t} - R_{P,t}$.

Time horizon $T > 0$ portfolio weights, given initial time-0 weights, then follow by recursion from Eq. (3) and by applying the functions $\ln(\cdot)$ and $\exp(\cdot)$ one after the other:

$$W_{i,T} = W_{i,0} \prod_{t=1}^{T} \exp\left(R_{\Delta,t}\right) = \exp\left[\ln\left(W_{i,0}\right) + \sum_{t=1}^{T} R_{\Delta,t}\right]. \tag{4}$$

Note that in order to have a proper weight $W_{i,T} \in [0; 1]$ above, a stopping time $1 \leq \tau \leq T$ condition with $W_{i,t} = 1$ for $t \in \{\tau+1, \dots, T\}$ is introduced and the stopping time is given by:

$$\tau = \max\left\{ t' \in \theta : \sum_{t=1}^{t'} R_{\Delta,t} \leq -\ln\left(W_{i,0}\right) \right\}.$$

Based on the given normality assumptions, $R_{\Delta,t}$ is also normally distributed with,

$$R_{\Delta,t} \sim \mathcal{N}(\mu_\Delta, \sigma_\Delta^2) = \mathcal{N}(\mu_i - \mu_P,\ \sigma_i^2 + \sigma_P^2 - 2\, \sigma_i\, \sigma_P\, \rho_{i,P}),$$

where $\rho_{i,P} \in [-1; 1]$ is the correlation between the returns of asset i and the portfolio P. The time-$(t-1)$ conditional expectation of future random portfolio weights that is derived from Eq. (3) is:

$$\mathbb{E}\left(W_{i,t} | \mathcal{F}_{i,t-1}\right) = W_{i,t-1}\, \mathbb{E}\left[\exp\left(R_{\Delta,t}\right) | \mathcal{F}_{i,t-1}\right] = W_{i,t-1} \exp\left(\mu_\Delta + 1/2\, \sigma_\Delta^2\right). \tag{5}$$

We can now characterize the long-run behavior of individual asset weights based on the return properties of the respective asset. Given that the condition, $\mu_\Delta + 1/2\, \sigma_\Delta^2 = 0$, on the expected return of asset i holds in Eq. (5), i.e. given that,

$$\mu_i = \mu_P - 1/2\, \left(\sigma_i^2 + \sigma_P^2 - 2\, \sigma_i\, \sigma_P\, \rho_{i,P}\right), \tag{6}$$

we have long-run weights for asset i, which obey the martingale property:

$$\mathbb{E}\left(W_{i,t}|\mathcal{F}_{i,t-1}\right) - W_{i,t-1} = 0. \tag{7}$$

In this equilibrium case we can assert that asset i is expected to be, in evolutionary wording,

- a "survivor" in portfolio P under Eq. (6), i.e. its long-run weight is expected to stay where it currently is.[6]
- However, when the relation is unequal in (6), asset i is characterized by positive or negative momentum.
- With the inequality $>$ in (6), positive momentum implies a submartingale case and asset i is going to be a "dominator" of the portfolio with $\{W_{i,t}\}_{t\in\theta} \to 1$, for $t \to \infty$, and
- when the inequality $<$ holds in (6), negative momentum yields a supermartingale and asset i is "threatened by extinction" with $\{W_{i,t}\}_{t\in\theta} \to 0$, for $t \to \infty$.

While these considered cases are obviously extreme limiting cases, our results underline that a significant violation of the equilibrium condition (6) is driven by more or less persistent and large momentum returns. These will eventually have effects on expected long-term portfolio weights. Assets threatened by extinction are the flip side of the coin of assets dominating the portfolio.[7]

1.2. Measuring investor crowding

Given the above section with the weights $W_{i,t}$ of the individual portfolio P assets $i = 1, \ldots, N$, we can now consider investor crowding $C_t(P)$ as measured through time. We want to measure crowding relative to a natural benchmark for portfolio diversification and therefore make the following proposition.

Proposition 1. ***Equal weights as a diversification benchmark***

Equal weights, $W_{i,t} = 1/N\ \forall i$, provide a natural prior in portfolio diversification. This is because

- *they are simple and straightforward to derive,*
- *they are a natural investment benchmark in absence of valid information on the future dependence structure of asset returns,*
- *they are not easy to beat ex-ante for market participants with average portfolio optimization skills as empirically shown by DeMiguel et al. (2007), and*
- *the fundamental concept of entropy suggests that equal weights represent an allocation with maximum obtainable diversification.*[8]

Given equal weights as our benchmark, entropy $\mathcal{H}$ allows us to measure the loss in diversification that the given weights of portfolio P induce. We accordingly define crowding by the degree it reduces diversification relative to the theoretical maximum diversification level. It formally follows:

$$C_t(P) \equiv \mathcal{H}_t(1/N) - \mathcal{H}_t(P). \tag{8}$$

Given this definition, we use entropy for a discrete set of random variables and relation (1) to derive our crowding measure. We have:

$$\begin{aligned} C_t(P) &= -\sum_{i\in\mathcal{U}} 1/N \ln(1/N) + \sum_{i\in\mathcal{U}} W_{i,t} \ln(W_{i,t}) \\ &= \ln(N) + \sum_{i\in\mathcal{U}} W_{i,t} \ln(W_{i,t}) \\ &= \ln(N) \sum_{i\in\mathcal{U}} W_{i,t} + \sum_{i\in\mathcal{U}} W_{i,t} \ln(W_{i,t}) \\ &= \sum_{i\in\mathcal{U}} W_{i,t} \left[\ln(N) + \ln(W_{i,t})\right]. \end{aligned}$$

Finally, we can use the following measure for time-t crowding in portfolio P:

$$C_t(P) = \sum_{i\in\mathcal{U}} W_{i,t} \ln(N W_{i,t}). \tag{9}$$

1.3. Crowding and constraints on asset risk premia

What happens when investor money is chasing select "hot" stocks? Investors focus their attention on a specific *identical* asset subset $\mathcal{S} \subset \mathcal{U}$ for which investment flows induce increased realized returns relative to the remainder assets. Considering condition (6), we have

$$\mu_i \gg \mu_P - 1/2\ \left(\sigma_i^2 + \sigma_P^2 - 2\,\sigma_i\,\sigma_P\,\rho_{i,P}\right), \qquad \forall i \in \mathcal{S}. \tag{10}$$

[6] Condition (6) shows that the main determinant is the asset's expected return that matches portfolio return expectation, while higher asset return volatility and lower asset correlation reduce the required expected return.

[7] Empirical evidence by Bessembinder (2018) shows that extinction of individual stocks in the U.S. market is quite common. The median time that a stock is listed on the Center for Research in Security Prices (CRSP) database during the years 1926 and 2016 is reported to be only seven and a half years.

[8] The concept is fundamental in theoretical physics and information theory, where Shannon (1948) introduced it to measure expected information that is transmitted by random signals.

In this setting, cross-sectional return heterogeneity will be higher than in a setting with less investor crowding. Condition (10) violates the weights martingale condition (7). Returns and changes in portfolio weights affect weight concentration and crowding is expected to increase over time. While moderate temporary levels of crowding can be assumed to be a common and inconspicuous phenomenon, the economic effects will become remarkable when crowding behavior becomes excessive. In the limit for $t \to \infty$, when (10) continues to hold with $|\mathcal{S}| = 1$, and asset i dominates all others, $\{W_{i,t}\}_{t\in\theta} \to 1$, crowding (8) will ultimately approach its theoretical maximum: $C_t(P) \longrightarrow \ln(N)$.

So what is a condition for non-crowded portfolios? In order to explain long-run portfolios which are balanced, we have to assert that a crowding condition as in Eq. (10) above can only hold temporarily. In other words, balanced long-run market portfolio proxies cannot exist under static risk premia assumptions. Instead, assuming time-varying expected asset returns, $\mu_{i,t}$, with constant risk exposures regarding $j = 1, \dots, M$ risk factors, $\beta_{i,j}$, a constant unexplained return α_i, and time-varying factor risk premia, $\lambda_{j,t}$, yields the representation: $\mathbb{E}\left(R_{i,t}|\mathcal{F}_{i,t-1}\right) = \mu_{i,t} = \alpha_i + \sum_j \beta_{i,j}\lambda_{j,t}$. We can now formulate the following proposition.[9]

Proposition 2. ***Sufficient conditions for weights martingales***

Absence of excessive crowding in the long run and existence of balanced market portfolio proxies can be obtained under the weights martingale condition. Given the above assumptions, sufficient conditions for (7) are that risk premia $\lambda_{j,t}$ obey the following properties. They

- *are time-varying and follow a stochastic process $\{\lambda_{j,t}\}$,*
- *are positively and negatively valued, $\lambda_{j,t} \in (-\infty; \infty)$, and they*
- *are mean reverting, such that for $t \to \infty$ we have returns that also mean revert, $\mu_{i,t} \to \mu_{i,\infty} = \mu_i$, where the mean reversion level is given by Eq. (6).*

The proposition forms a general hypothesis on the cross-section of asset returns and relates to a large body of empirical asset pricing research. We briefly refer to some of the stylized facts as follows.

- The observation of long-run mean reversion in stock returns and prices is empirically well-established De Bondt and Thaler (1985), Fama and French (1988) and Poterba and Summers (1988). However, it seems that the consequences were not debated in the asset pricing literature.
- Recent studies, including Haddad et al. (2020), Hughson and Wallace (2023), Jacobson and Lee (2021) and Li et al. (2026), point to the time-varying nature of factor risk premia.
- There is also evidence that the value premium varies over time (Fama and French (2021)).
- The momentum effect can be consistent with a balanced market proxy given that it is interrupted by periods of a significant negative realized momentum premium as documented e.g. by Daniel and Moskowitz (2016).
- Assuming that small capitalization firms tend to replace larger capitalization firms in a market portfolio proxy through time – i.e. portfolio additions tend to be small, while deletions tend to be bigger – a fixed size premium according to Banz (1981) may be consistent with a balanced market proxy.

2. Empirical illustration

Given our above derivations, we illustrate investor crowding behavior over time and its potential relation to economic and financial uncertainty. Fig. 1 plots our monthly Standard and Poor's 500 index crowding measure as given by Eq. (9) during the period from January 1990 to December 2024. We define regimes using the empirical distribution: low crowding is the bottom decile (below 0.6552), high crowding is the top decile (above 0.9715), and medium crowding includes all remaining months. Crowding is cyclical and varies substantially over time. High levels of crowding indicate that diversification is affected and index portfolios are effectively unbalanced, with returns driven by a small dominant subset of stocks.

As shown in Fig. 1, crowding is most pronounced during the Dot Com Bubble and again in several 21st-century episodes in which capital tends to concentrate in market segments. In recent years, the crowding measure rises steadily, accelerates, and reaches its absolute maximum at the end of 2024. This indicates the remarkable dominance of the mega-cap stocks in the high-crowding regime that is not only more pronounced, but also more persistent than any of the earlier concentration episodes. Descriptive statistics of the crowding measure are presented in Table 1. Crowding is non-normally distributed with a distinct positive skew, a mean of about 0.78, a minimum of 0.62 and a maximum of 1.21.[10] As a matter of fact, the measure is highly persistent with an estimated first-order autocorrelation coefficient of 0.999 ($p < 0.001$) and non-stationary according to the augmented Dickey–Fuller test ($p = 0.9844$).

We hypothesize that macroeconomic and uncertainty shocks induce adjustments in investor behavior, potentially affecting both risk aversion and crowding through portfolio reallocation. The macroeconomic controls and uncertainty proxies are listed in Table 1. While correlations suggest systematic links between shocks in these variables and crowding, full sample multivariate regressions do not indicate a close linear relation.

[9] An alternative proposition would set factor premia constant and make comparable assumptions on time-varying risk factor exposures, or include both, time-variation in factor premia and exposures.

[10] The theoretical upper limit for crowding in the index is given by $\ln(500) \approx 6.22$ and the crowding distribution has limited support: $C_t(S\&P) \in [0; 6.22]$. The crowding data are available for download at https://www.wiwi.uni-passau.de/finanzcontrolling/forschung/crowding.

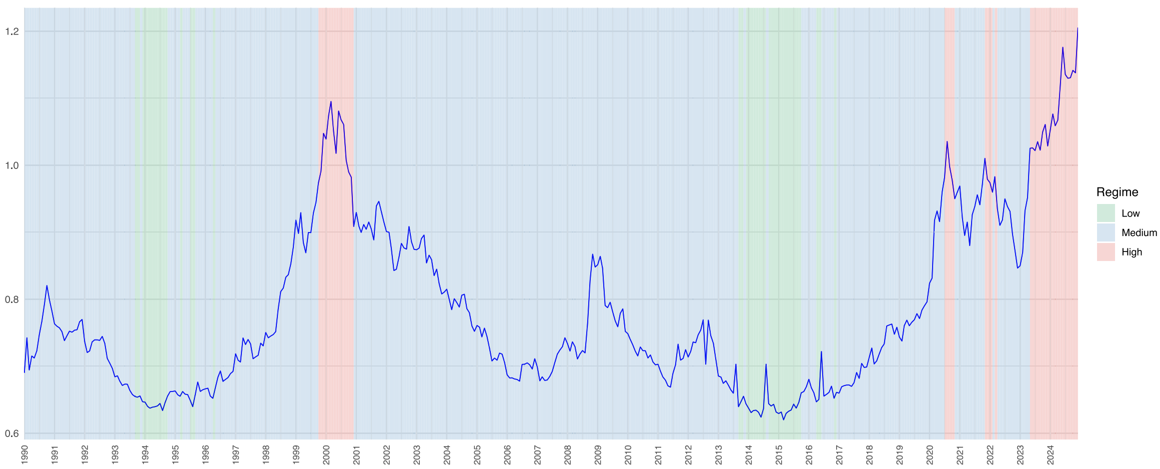

Fig. 1. U.S. stock market crowding regimes.
Monthly index crowding based on S&P 500 constituents from January 1990 to December 2024. Shaded areas indicate regime classifications based on the empirical distribution of the crowding measure: low (bottom decile), medium (intermediate) and high (top decile). The crowding data are available at: https://www.wiwi.uni-passau.de/finanzcontrolling/forschung/crowding.

Table 1
Descriptive statistics and correlations of ΔCrowding with macro and uncertainty variables.

Descriptive statistics			Correlations with ΔCrowding		
	Crowding	ΔCrowding	Variable	ρ	p-value
Mean	0.7816	0.0012	ΔVIX	0.2360	(0.0000)***
Median	0.7395	0.0007	ΔFED	−0.0844	(0.0843)*
SD	0.1261	0.0214	ΔCPI	−0.0071	(0.8846)
Min	0.6199	−0.0735	ΔTERM	0.0695	(0.1556)
Max	1.2055	0.0863	ΔDEF	0.1447	(0.0030)***
Skewness	1.0202	0.3505	ΔUMC	−0.1783	(0.0002)***
Kurtosis	3.2439	5.3898	ΔGPR	0.0871	(0.0749)*
Jarque–Bera	73.73	108.28	ΔEPU	0.1326	(0.0066)***

The sample covers monthly observations of the crowding measure (level and first difference) from January 1990 to December 2024. Macroeconomic variables and uncertainty proxies used in our empirical analysis are the federal funds rate (FED), inflation (CPI), the term spread (TERM), credit risk (DEF), consumer uncertainty (UMC), implied stock market volatility (VIX), economic policy uncertainty (EPU), and geopolitical risk (GPR). Pearson correlations are reported with p-values in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2
Regression results of ΔCrowding on lagged macroeconomic and uncertainty shocks.

Threshold	Full sample	Low	Medium	High
	–	x ≤ 0.6552	$0.6552 < x < 0.9715$	x ≥ 0.9715
Intercept	−0.00004 (0.9771)	−0.00904 (0.0018)***	0.00051 (0.7025)	−0.00132 (0.8884)
ΔVIX_{t-1}	0.00032 (0.2497)	−0.00033 (0.7620)	0.00063 (0.0307)**	−0.00527 (0.0026)***
ΔFED_{t-1}	0.2349 (0.7215)	2.3960 (0.0072)***	0.0178 (0.9795)	5.0761 (0.1856)
ΔCPI_{t-1}	0.00258 (0.1412)	0.00658 (0.1329)	0.00115 (0.6199)	0.00712 (0.2777)
$\Delta TERM_{t-1}$	0.00297 (0.6844)	−0.0301 (0.1472)	−0.00219 (0.7895)	0.0515 (0.0082)***
ΔDEF_{t-1}	0.00449 (0.7151)	0.0220 (0.5884)	−0.00085 (0.9462)	−0.02397 (0.7513)
ΔUMC_{t-1}	0.00020 (0.4141)	0.00070 (0.0665)*	0.00003 (0.9081)	0.00219 (0.1289)
ΔGPR_{t-1}	0.00002 (0.4698)	−0.00010 (0.3952)	0.00001 (0.5382)	0.00039 (0.0090)***
ΔEPU_{t-1}	0.00004 (0.2618)	0.00008 (0.1374)	0.000003 (0.9425)	0.00022 (0.0341)**

Regression estimates of ΔCrowding on lagged macroeconomic and uncertainty shocks. Coefficients are estimated for the full sample and across crowding regimes. The regime classification is based on the distribution of the crowding measure (bottom 10% quantile, top 10% quantile and intermediate observations). Coefficients are reported with p-values based on Newey–West standard errors in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3
Asymmetric effects of uncertainty shocks on ΔCrowding.

	β^+ (Up)		β^- (Down)	
ΔVIX_{t-1}	0.00075	(0.0123)**	0.00008	(0.8700)
ΔEPU_{t-1}	0.00008	(0.2330)	−0.00003	(0.5950)
ΔGPR_{t-1}	0.00002	(0.3140)	−0.00006	(0.2300)
ΔUMC_{t-1}	0.00044	(0.3590)	0.00046	(0.2970)

Results from regressions of ΔCrowding on positive (β^+) and negative (β^-) components of lagged uncertainty shocks. *P*-values based on Newey–West standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

As shown in Table 2, regime-specific estimates confirm state dependence. When concentration is moderate, VIX shocks increase crowding as investors shift capital toward a narrower set of supposedly resilient stocks. When concentration is high, VIX shocks reduce crowding as investors tend to rebalance away from dominant positions which represent a potential concentration risk. Moreover, effects differ by shock type: VIX captures short-term price uncertainty and triggers immediate rebalancing, whereas EPU and GPR reflect changes in broader macroeconomic expectations.

Crowding responds selectively to uncertainty, with different shocks translating into different reallocation patterns and cross-sectional return heterogeneity. As such, Table 3 indicates asymmetric effects of the VIX on crowding. Positive shocks raise concentration, whereas negative shocks do not produce a corresponding symmetric decline. Hence, positive shocks drive investors toward a narrower selection of assets, but negative shocks do not automatically lead to a reversal of this behavior. Therefore, it seems plausible that a series of positive VIX shocks goes along with increased investor crowding. By contrast, EPU and GPR show no comparable asymmetries, suggesting that those risks are incorporated in a more balanced way. Overall, our results support the view that crowding can be seen as a state-dependent outcome of uncertainty shocks that induce adjustments in market concentration.

3. Conclusion

In the present work, we examine the properties of asset portfolio weights and use them for measuring investor crowding behavior. Crowding can be considered as important in finance research as intense crowding will violate optimal diversification properties of capitalization weighted market portfolio proxies. These, such as the Standard and Poor's 500 index, matter for modern economies' savings allocations as they form benchmarks for vast institutional and individual investments worldwide.

From our considerations it also follows that constant equity risk premia would yield dominated long-term portfolios and are therefore generally at odds with balanced market portfolio proxies. Put differently, observing relatively balanced long-term portfolio compositions can be seen as consistent with risk premia, which are time-varying and mean reverting. Further research is needed to reject or validate our hypotheses.

Credit authorship contribution statement

Patrizia Perras: Writing – original draft, Methodology, Visualization, Data curation, Software, Writing – review & editing.
Niklas Wagner: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

Data availability

The crowding data are available at: https://www.wiwi.uni-passau.de/finanzcontrolling/forschung/crowding.

References

Banz, R.W., 1981. The relationship between return and market value of common stocks. J. Financ. Econ. 9, 3–18.
Bessembinder, H., 2018. Do stocks outperform treasury bills? J. Financ. Econ. 129, 440–457.
Brown, G., Howard, P., Lundblad, C.T., 2022. Crowded trades and tail risk. Rev. Financ. Stud. 35, 3231–3271.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Financ. 24, 1651–1679.
Christie, W.G., Huang, R.D., 1995. Following the pied piper: Do individual returns herd around the market? Financ. Anal. J. 51, 31–37.
Daniel, K., Moskowitz, T.J., 2016. Momentum crashes. J. Financ. Econ. 122, 221–247.
De Bondt, W.F.M., Thaler, R., 1985. Does the stock market overreact? J. Financ. 40, 793–805.
DeMiguel, V., Garlappi, L., Uppal, R., 2007. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? Rev. Financ. Stud. 22, 1915–1953.
Fama, E.F., French, K.R., 1988. Permanent and temporary components of stock prices. J. Politi. Econ. 96, 246–273.
Fama, E.F., French, K.R., 2021. The value premium. Rev. Asset Pricing Stud. 11, 105–121.
Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27, 714–746.
Haddad, M., Kozak, S., Santosh, S., 2020. Factor timing. Rev. Financ. Stud. 33, 1980–2018.
Hughson, E., Wallace, J., 2023. The anti-ESG equity premium. Working Paper, Claremont McKenna College.
Jacobson, B., Lee, W., 2021. Macroeconomics and the value premium. J. Asset Manag. 22, 241–252.
Kwan, A., Liu, Y., Matthies, B., 2026. Institutional investor attention. J. Financ. (Forthcoming).
Li, S., Yuan, P., Zhou, G., 2026. Episodic Factor Pricing. Working Paper, Washington University in St. Louis.

Menkveld, A., 2017. Crowded positions: An overlooked systemic risk for central clearing counterparties. Rev. Asset Pricing Stud. 7, 209–242.
Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867–887.
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. J. Financ. 42, 483–510.
Pedersen, L., 2009. When everyone runs for the exit. Int. J. Central Bank. 5, 177–199.
Poterba, J.M., Summers, L.H., 1988. Mean reversion in stock prices: Evidence and implications. J. Financ. Econ. 22, 27–59.
Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27, 379–423.
Stein, J.C., 2009. Sophisticated investors and market efficiency. J. Financ. 64, 1517–1548.
Stutzer, M.J., 2010. The paradox of diversification. J. Invest. 19, 32–35.
Wagner, N., 2002. On a model of portfolio selection with benchmark. J. Asset Manag. 3, 55–65.