Crowding and Tail Risk in Momentum Returns

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Abstract

Several theoretical studies suggest that coordination problems can cause arbitrageur crowding to push asset prices beyond fundamental value as investors feedback trade on each others’ demands. Using this logic, we develop a crowding model for momentum returns that predicts tail risk when arbitrageurs ignore feedback effects. However, crowding does not generate tail risk when arbitrageurs rationally condition on feedback. Consistent with rational demands, our empirical analysis generally finds a negative relation between crowding proxies constructed from institutional holdings and expected crash risk. Thus our analysis casts both theoretical and empirical doubt on crowding as a stand-alone source of tail risk.

I. Introduction

What is the role of crowding in generating tail risk in investment strategies? A growing theoretical literature argues that financially constrained arbitrageurs can generate tail risk in asset prices by way of fire sales (forced exit from an otherwise profitable trade). The constraints underlying these theories derive from a variety of sources, including delegated portfolio management (Shleifer and Vishny (1997)), segmented margin accounts (Gromb and Vayanos (2002)), self-imposed loss limits (Morris and Shin (2004)), and illiquidity in funding markets (Brunnermeier and Pedersen (2009)). Crowding potentially plays an interactive role in these theories by setting the conditions under which a forced reversal of investment positions.

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generates extreme price impact and transient undervaluation. Indeed, Brown, Howard, and Lundblad (2019) provide empirical support for the hypothesis that concentrated positions amplify tail risk in times of market distress.

The aim of this study is rather different. We explore whether crowding per se generates tail risk, without conditioning on market distress. As developed below, such an analysis requires a setting in which arbitrageurs follow a strategy based on prices and incomplete information about peer actions; and a setting where crowding induced tail risk is plausible. The momentum strategy fits that setting well. It uses no exogenous signal of value that could be used to coordinate arbitrage, and it is a statistically robust, widely documented, and popular investment strategy that has well-known crash tendencies (Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016)). Related studies have shown that incomplete information about the actions of peers (i.e., the crowd) can induce arbitrageurs to amplify bubbles (Abreu and Brunnermeier (2003)) and push prices away from fundamental value (Stein (2009)). We contribute to this literature by formally developing a theory of crowding and momentum tail risk, and conducting an empirical analysis of that theory using direct measures of institutional crowding applied to 13f data.

Our theoretical setting uses standard assumptions for preferences and the structure of information to highlight the central role of investors’ beliefs. We first demonstrate how unobserved crowding can explain momentum tail risk using the logic of Stein (2009). If the demands of peer momentum investors are indistinguishable from the informed trade that the strategy seeks to exploit, then unanticipated entry by those peers can create a feedback component to each momentum investor’s demand. Depending on how beliefs are structured, this feedback component can spiral into grossly inflated aggregate momentum demands, driving the market price of momentum stocks far beyond their fundamental value. The extreme valuation reverses with the arrival of fundamental information, yielding large negative momentum returns. This motivates a crowding hypothesis for momentum crashes.

We then demonstrate that this crowding hypothesis requires myopic momentum investors. If momentum investors ignore feedback effects then, under standard assumptions, their demands relate linearly to market prices. However, linear demands generate precisely the feedback effects that momentum investors ignore in forming linear demands. Because those feedback effects are nonlinear, rationality requires a nonlinear mapping from market prices to the inferred fundamental values. This in turn implies nonlinear demands. In our rational solution to market equilibrium, we solve for these demands using conditional expectations derived from a fixed-point equilibrium condition. We find that the resulting demands eliminate crowding-induced momentum tail risk.

This sets up the primary test in our empirical analysis. If we can relate crowd size to tail risk in momentum returns, then we ought to also be able to find feedback effects in momentum investors’ demands. Conversely, if we are unable to link crowding to negative skewness in momentum returns, then we should find that momentum investors exit from the momentum strategy when feedback risks are high. This unwinding of feedback effects via risk-managed demands is the main insight from the rational expectations equilibrium, which predicts that momentum investors negate crowding effects by reducing demands when feedback risks are high.
Our empirical analysis uses 13f data to construct proxies for momentum crowding by directly linking changes in institutional holdings to past returns, following the analysis of mutual fund momentum trading in Grinblatt, Titman, and Wermers (1995). However, our proxies incorporate persistence in trading to better distinguish investment strategy from spurious trade-return correlations. Also, we consider a variety of perspectives on identifying crowd size, including the number of momentum investing institutions, their size, and the aggregate intensity of their trade. We consider a perspective that focuses on the momentum factor mimicking portfolio and a perspective that focuses on individual momentum stocks. To the best of our knowledge, this represents the most direct and comprehensive construction of proxies for institutional momentum investing in the literature. Several other studies (most notably Lou and Polk (2013)) use returns-based approaches to infer crowding. We provide evidence on the efficacy of returns-based procedures relative to our direct proxies based on institutions’ trading strategies.

We find strong evidence that crowding predicts negatively mean momentum returns, which is consistent with theoretical prediction under all belief specifications considered. However, we find little evidence that (unanticipated) crowding predicts momentum tail risk. To be meaningful, tail risk implies negative skewness, elevated volatility, and excess kurtosis. Our proxies for momentum crowding generally relate negatively to all 3,¹ often with statistical reliability. This result is not consistent with crowding providing a stand-alone explanation for momentum crashes, but it is consistent with our rational expectations model of momentum investing. In particular, our finding of reduced participation by institutional momentum investors when feedback risks are high supports the rational model’s premise. Thus, we reject crowding as a stand-alone explanation for momentum tail risk.

A link between crowded trades and higher return moments for quantitative investment strategies such as momentum has been examined in the context of the “quant meltdown” of 2007 (e.g., Khandani and Lo (2007), Pedersen (2009)). It is important to note that these studies analyze the interactive effect of crowded strategies on funding liquidity risks; they do not argue that crowding per se led to the meltdown. This is a different model of tail risk (deriving from funding liquidity) than that considered here (deriving from feedback effects). Our analysis concludes that crowding does not provide a stand-alone explanation for momentum tail risk. We do not consider the role of funding liquidity, or how funding interacts with the extent of institutional participation in the momentum strategy.

Our analysis makes an important contribution to the literature on risk management in investment strategies (e.g., Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016)). Our theory provides intuition in the context of a rational expectations model, and our empirical evidence demonstrates how momentum institutional investors pull back from the strategy in toxic environments. Our assumptions are conventional. We use log normally distributed cash flows and constant relative risk aversion (CRRA) preferences with a second-order approximation in the demand optimization (as in Campbell and Viceira (2002), Peress (2004)); that is,

¹To be precise, crowding is associated with lower volatility, less excess kurtosis, and less negative skewness.
effectively mean–variance preferences scaled to wealth. Our information structure is similar to Hong and Stein (1999) and Stein (2009), from which the crowding hypothesis arguably originates. Finally, our fixed-point methodology does not put restrictive conditions on the distribution of cash flows or the mapping of cash flow expectations into demands. Thus, it is robust to alternative specifications.

On the empirical side, several arguments speak in favor of our crowding measures. First, the measures draw on a large body of literature that shows that institutional investors are momentum traders (Lewellen (2011), Edelen, Ince, and Kadlec (2016)). Second, we verify with transition matrices that our institution-level measures capture meaningful momentum trading. Finally, our first main empirical results show that our crowding proxies indeed strongly negatively relate to momentum returns, even after controlling for momentum’s volatility (Barroso and Santa-Clara (2015)) and dynamic risk factors (Grundy and Martin (2001)).

We try to reconcile our results with studies that use returns-based measures of crowding. For the momentum gap measure proposed by Huang (2022), we show that orthogonalizing this variable to our crowding measures leaves the ability to predict momentum tail risk unaffected. This supports our second main empirical conclusion that momentum’s crash risk cannot be attributed to crowding by institutional investors, and it opens the door to alternative explanations for momentum crashes.2

There is much related literature on the subject. We provide a detailed survey in Supplementary Material Section IA.A. Section II develops the model and Section III develops and analyzes its result using a simulation approach. Section IV presents the empirical analyses and Section V concludes the study.

II. Model

A. Setting

In practice momentum is a dynamic strategy that conditions on past (realized) returns. To focus on the effect of crowding, we collapse the analysis into a single call auction as in Stein (2009).3 Thus, we model a 2-period setting where the first period generates a formation-period return and the second period generates an evaluation-period return. In the first period, informed investors observe a signal of differential value for good versus bad stocks, and in the second period, the fundamental value of all stocks is revealed. As developed below, this setting gives rise to momentum returns similar to Stein (2009).

The setting at time 0 is symmetric in that all stocks have equal market value and all investors hold the same portfolio: an equal-weighted investment in all stocks. There are 3 types of stocks; good, bad, and neutral, but at time 0, no investor

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2See, for example, Daniel, Jagannathan, and Kim (2019) who argue that momentum crashes arise because of the higher effective leverage of past loser stocks (in the sense of Merton (1974)) following market downturns.

3Since investors can submit a demand schedule that conditions on the market clearing price at the time of the auction, they can effectively condition on past returns as of that time – even though demand schedules are submitted prior to the auction. Our simplified setting therefore retains the key feature of the momentum strategy.
knows their identity. There are 3 types of investors: informed, momentum, and counterparty. During the formation period (time 0–1) informed investors observe the type of each stock, and a valuation signal $\delta$ described below. This signal indicates the differential payoff on good versus bad stocks. All good stocks have the same positive signal and all bad stocks have the same negative signal.

The fundamental value $P_{j,2}$ of each stock $j$ is revealed to all investors at time 2 to be

$$\ln P_{j,2} = \ln P_{j,0} + \chi + \eta_j \frac{\delta + \epsilon}{2},$$

where $P_{j,0}$ is the time-0 price that is normalized to 1 without loss of generality; $\chi$ is a normally distributed mean-zero innovation common to all stocks with variance $\sigma^2$; $\eta_j$ identifies stock $j$’s type (1 for good, $-1$ for bad, and 0 for neutral); and $\delta + \epsilon$ is the realized valuation spread on good minus bad stocks that consists of the signal $\delta$ and a normally distributed mean-zero disturbance $\epsilon$ with variance $\sigma^2$. The random variables $\chi$, $\delta$, and $\epsilon$ are independent. $\chi$ generates market risk for investors, whereas $\delta + \epsilon$ generates a momentum return as developed below.

Informed investors see the vector of stock identifiers $\{\eta_j\}$ in the formation period, and their signal $\delta$ that is drawn from a lognormal distribution. Thus, $\delta$ (which can be thought of as the ex ante valuation spread on good stocks minus bad) is positive, whereas $\delta + \epsilon$ (the ex post spread) can be negative.

Informed investors seek to trade in the time 1 call auction. However, because of their signal homogeneity, their demands can be condensed to an equal-weighted portfolio that is long all good stocks and short all bad stocks. This defines the momentum portfolio. Momentum investors infer the portfolio from the differential price pressure of informed demands.

Both counterparty and momentum investors remain uninformed in the formation period. Thus, neither would be willing to counter demands in the time 1 auction if they were rational and knew that informed investors were active. To support market clearing, we therefore define a counterparty investor type that irrationally fixates on historical data and ignores the existence of $\delta$ (effectively assuming $\delta = 0$). As a result, these investors wrongly interpret informed investors’ price pressure as noise, so they trade counter to that price pressure in the time 1 call auction.

Our third investor type, momentum investors, recognizes that the above two investor types generate equilibria with momentum opportunities if informed investors are risk averse. Thus, momentum investors formulate a model of market equilibrium in the time 1 call auction and use that model to try to capture momentum opportunities. In doing so, they incorporate varying degrees of rationality into their model. They know the distribution of random variables.

Note that every investor trades a single basket: the momentum portfolio. Informed investors do so because of their homogeneous signal. Counterparty and momentum investors do so because they react to the pricing signal caused by

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4Counterparty investors can also be thought of as contrarian traders anchoring on past prices. See, for example, Hvidkjaer (2006) for empirical evidence on contrarian trading and George and Hwang (2004) for evidence showing that traders likely anchor on past prices.
Informed investor demands. We therefore frame our analysis in terms of the momentum portfolio as a single, composite asset.

Let $f$ denote the formation-period log return on the momentum portfolio (to be solved for). The evaluation period log return is then $\delta + \varepsilon - f$. Let $m \equiv E(\delta + \varepsilon - f | \delta, f) = \delta - f$ denote the expected momentum return that informed investors leave on the table in the time 1 call auction. Only informed investors see $m$.

### B. Demand Schedules

All investors have power utility preferences with relative risk aversion $\gamma$, choosing a time 1 demand schedule for the momentum portfolio to maximize

$$
E[u(K_2)] = E \left[ \frac{K_2^{1-\gamma}}{1-\gamma} \right],
$$

where $K_2$ denotes their time 2 capital. We use the second-order approximation approach of (Campbell and Viceira (2002), Internet Appendix) to restrict investors’ attention to the first 2 moments, yielding

$$
Demand = \frac{E_{type}[m + \varepsilon]}{\gamma Var_{type}[m + \varepsilon]} K_{type,0},
$$

where $K_{type,0}$ denotes the time 0 initial capital of the indicated investor type $\in \{I, C, M\}$, and the details of the derivation are in Supplementary Material Section IA.B. The expectations can be simplified to $E_I[m + \varepsilon | \delta, f] = \delta - f$, $E_C[m + \varepsilon | f] = -f$, and $E_M[m + \varepsilon | f] = \delta^E - f$. The variances are $Var_I[m + \varepsilon | \delta, f] = \sigma^2_\varepsilon$, $Var_C[m + \varepsilon | f] = \sigma^2_\varepsilon$, and $Var_M[m + \varepsilon | f] = \delta^V + \sigma^2_\varepsilon$. The placeholders $\delta^E = E_M[\delta | f]$ and $\delta^V = Var_M[\delta | f]$ will thereby be solved for below.

Momentum investors infer expected momentum returns, $m$, by way of the market clearing price. This inference is imperfect and potentially quite complicated since market equilibrium depends on unobservable capital allocations and momentum investors’ own demands.

### C. Equilibrium

Summing demands across the 3 investor types and equating to supply (zero) gives the market clearing condition:

$$
f = \frac{1}{D} \left( \delta k_I + \frac{\delta^E}{1 + \frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon}} k_M \right),
$$

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5We assume that $\gamma > 1$ without loss of generality throughout the paper.

6The advantage of this scheme over CARA utility is to provide a natural role for investors’ capital to frame the analysis of crowding. We acknowledge that the analysis would probably not differ substantially if we were to begin with CARA preferences.

7To this point, our analysis largely parallels Stein (2009). Our analysis of varying degrees of rationality, including a fully rational fixed-point equilibrium, marks the point of departure.
where $D = \left(1 - \frac{\delta}{\sigma^2 + \delta} k_M\right)$ and $k_{\text{type}} = K_{\text{type}} / (K_C + K_1 + K_M)$ indicates the fraction of capital from each investor type. The random variable $k_M$ is the momentum-investor relative crowd size.\(^8\) The initial capital allocations $k_1$, $k_C$, and $k_M$ are randomly drawn from a symmetric Dirichlet distribution (discussed in more detail in Section III).

We consider 4 solutions to equation (4), beginning with a perfect-information base case and continuing through various assumptions on momentum investor rationality.

1. **Known Crowding**

   With known crowding (i.e., the realization of random variables $k_M$ and $k_1$ are observed prior to trading) momentum investors conjecture a linear equilibrium

   \[ f = \lambda \delta, \]  

   with $\lambda = k_1 + k_M$. Beliefs $\delta E = \lambda^{-1} f$ and $\delta V = 0$ lead to a self-fulfilling linear solution to equation (4). Hence, momentum investors’ conjecture fully reveals the private signal of informed investors.

2. **Myopic Beliefs**

   This case assumes that momentum investors know the mean of the distribution of capital allocations, but they neither observe realizations, nor do they attempt to infer realizations from market prices. They trade as if capital allocations were at their unconditional mean values, conjecturing a linear equilibrium pricing relation

   \[ f = \lambda \delta, \quad \text{where} \quad \lambda \equiv Ek_M + Ek_1, \]  

   as in the known-crowding case. The market clears at

   \[ f = \lambda \left( \frac{k_1}{\lambda - k_M} \right) \delta = \lambda \left( \frac{k_1}{Ek_1 - (k_M - Ek_M)} \right) \delta. \]  

   The bracketed multiplier in equation (7) equals 1 when realized capital allocations happen to equal their expected values, but it generally adds a noise component to $\delta$ with unanticipated crowding (as in Stein (2009)). As momentum investors react to this false momentum signal, their demands generate an asymmetric crowding-induced feedback effect. This distortion is rather immaterial when the crowd size is abnormally low, but an abnormally high crowd size can drive the price of the momentum portfolio far beyond fundamental value. The result is a momentum crash when fundamental value is revealed.\(^9\)

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\(^8\) Note that crowding is not the same as aggregate demand by momentum investors for the momentum portfolio, which follows from equation (3). This is an important distinction for the empirical section: Crowding uncertainty derives from not knowing how many peers are following the same strategy. To quote Stein ((2009), p. 1530), “…each arbitrageur is uncertain about how many [emphasis not added] others will act.”

\(^9\) There is an equilibrium at a finite negative value for $f$ when $k_M > \lambda$. This corresponds to a reversal of identification on winners and losers, putting momentum investors on the wrong side of the trade (heavily buying losers and selling winners, with informed traders taking the other side and making enormous
3. Optimal Linear Beliefs

This is an intermediate stop on the road to rationality, considered in Stein (2009). As in the myopic case, momentum investors make no attempt to infer realized capital allocations from the market clearing price, despite the asymmetric (and occasionally extreme) impact that crowding can have on that price. That is, as the market clearing price $f$ becomes more extreme, it becomes more likely that its source is crowding-induced feedback effects rather than information. When momentum investors restrict their strategy space to linear beliefs, $\delta^E = \lambda^{-1} f$, they ignore this characteristic of market equilibrium. This is the case considered here.

Thus, momentum investors maintain a linear strategy, as in the myopic case, but they apply an ad hoc attenuation to $\lambda^{-1}$ to maximize ex ante profits (conditional on linear beliefs). This yields an equilibrium that is structurally similar to equation (7), but with enough attenuation the denominator in the bracketed multiplier can be bounded away from zero. This prevents catastrophic losses from crowding-induced feedback effects.

4. Rational Beliefs

To be rational, when beliefs $\delta^E$ and $\delta^V$ condition on $f$ they must generate demands that clear the market at $f$. That is, they provide a fixed point solution. Optimal linear demands do not satisfy this condition.

Rationality is easily attained in the case of known crowding. Here, we show that it is also attainable with unknown crowding. The only requirement is that momentum investors account for the asymmetric signal that $f$ provides regarding the presence of crowding-induced feedback effects. The random variables in the system are $\delta$, $k_1$, and $k_M$. We write their joint density as $g(\delta) \cdot h(k_M,k_1)$, since $\delta$ is independent of $k_M$ and $k_1$ but the $k$’s themselves are dependent (with $k_C$ they sum to 1 and are nonnegative). Momentum investors compute $\delta^E$ and $\delta^V$ given this joint density, observation of $f$, and the definition of conditional expectations:

$$\delta^E = \int_0^\infty \delta p(\delta|f) d\delta,$$

and

$$\delta^V = \int_0^\infty (\delta - \delta^E)^2 p(\delta|f) d\delta,$$

where, as shown in Supplementary Material Section IA.D,

$$p(\delta|f) = \frac{g(\delta) \int_0^1 h\left(k_M, \frac{1}{\delta} \left(fD - \frac{\delta^E}{1+(\delta^E/\sigma^2)}k_M\right)\right) Ddk_M}{\int_0^\infty g(\delta) \int_0^1 h\left(k_M, \frac{1}{\delta} \left(fD - \frac{\delta^E}{1+(\delta^E/\sigma^2)}k_M\right)\right) Ddk_M d\delta}.$$

We use Matlab’s FSolve function to jointly solve equation (8) and density function (9) at a given value for $f$. We then repeat over a fine grid of plausible values for $f$ to discretely approximate the mappings $f \rightarrow \delta^E$ and $f \rightarrow \delta^V$. We then interpolate to approximate beliefs at arbitrary values of $f$.10

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10 We do not presume that investors literally solve equation (8) in practice. Rather, the assertion is that the market equilibrium that results from their trades aligns with this formula. Likewise, the
III. Simulations

In this section, we analyze the equilibrium under each specification of beliefs by solving equation (4) 100,000 times with 100,000 random draws of the market conditions (i.e., \( \delta \), \( k_M \), and \( k_I \)) in each of the 4 belief cases. We then use those 100,000 equilibria per case to evaluate momentum return moments and belief consistency. We use a concentration parameter \( \alpha = 3 \) in the symmetric Dirichlet distribution for capital proportions, \( \text{Dir}(\alpha) \). This provides a relatively diffuse prior belief for crowding, while maintaining a natural dependence among fractions of a whole with equal expected value 1/3 and vanishing probability that \( k_{\text{type}} = 0 \) or 1.\(^{11}\)

We use a mean (standard deviation) of \(-2.405 (0.125)\) in the log-normal distribution for \( \delta \),\(^12\) and \( 0 (0.125) \) in the normal distribution for \( \epsilon \). These calibrations are designed to fit summary characteristics of momentum returns.\(^{13}\) Table 1 provides descriptive statistics of simulated momentum returns and Figure 1 provides graphs of momentum investors’ inference of the informed signal, \( \delta^E \), and the expected momentum returns \( m \) given that signal. The first 4 columns in Table 1 and graphs in Figure 1 correspond to the base case (known crowding), the rational, the myopic, and the optimal linear setting; left to right, respectively. To construct the graphs, simulation trials are ranked into 100 bins according to the conditioning variable on the horizontal axis and the 1,000 trials within each bin are averaged to approximate a conditional expectation. Table 1 also includes a fifth column tabulating summary characteristics of actual momentum returns for comparison.

Graphs A.1, B.1, C.1, and D.1 in Figure 1 examines the rationality of beliefs: whether or not momentum investors’ presumed belief of \( \delta \) (\( \delta^E = \) horizontal axis) is consistent with the average realized \( \delta \) (vertical axis) in the corresponding simulations. Rationality implies an identity (i.e., momentum investors are correct on average). A wider (narrower) spread on the vertical axis implies that momentum investors successfully infer more (less) information.

Graphs A.2, B.2, C.2, and D.2 present the expected momentum return \( m \) as a function of beliefs, \( \delta^E \). A negative \( m \) means that momentum investors have systematically pushed the price of momentum stocks beyond their fundamental value. Hence, these graphs identify settings in which momentum investing generates destabilizing crowding effects.

\(^{11}\)In Supplementary Material Section IA.E, we find qualitatively similar predictions under various permutations on \( \alpha \) and other characteristics of the presumed setting, such as a uniform distribution for \( \delta \).

\(^{12}\)These values imply an average \( \delta \) of 9.1% with standard deviation of 1.14%. The log-normal distribution has the advantage that the differential dividend is limited to positive values, and this distributional assumption is consistent with the evidence in Andersen, Bollerslev, Diebold, and Ebens (2001).

\(^{13}\)The model’s aim is to analyze whether market equilibrium in the presence of unanticipated crowding generates tail risk in momentum returns. The most salient way to do this is to presume a setting where there is no tail risk in the primitive distribution for cash flows, and analyze whether or not market equilibrium creates it. However, if we were to simulate a setting with tail risk in the residual, our simulated equilibria would be unaffected, as the model essentially employs mean–variance demands scaled to wealth (given our use of the Campbell and Viceira (2002) approximation).
A. Base Case (Known Crowding)

The base case presumes that momentum investors know the degree of crowding from competing momentum investors at the time of trade. This allows perfect coordination of demands so there are no crowding effects. We use the resulting distribution of momentum returns as our benchmark for evaluating the more interesting cases in which investors must form beliefs for unknown crowding.

From column 1 in Panel A of Table 1, note that expected momentum returns $m$ in this base case are close to normally distributed with some positive skewness, and are never negative; momentum investors never overshoot informed investors’ signal because they can perfectly infer it from the market clearing price. Nevertheless, from Panel B of Table 1, realized momentum returns $(m + \epsilon)$ are frequently negative. From the fifth column, note that modeled realized returns in the base case roughly match the empirical mean and variance of quarterly momentum returns, indicating that our assumed distribution of model inputs is well calibrated. However, in contrast to the empirical distribution of momentum returns, modeled returns are essentially normally distributed with no excess tail risk.

Table 1 also presents the simulated profitability of momentum, both as a mean abnormal portfolio return (“mean profit”) and a certainty-equivalent return. Profitability takes into account both the momentum return and the magnitude of the position taken in the momentum portfolio. Mean profits in the base case are slightly less and the certainty equivalents slightly more than the corresponding empirical mean and certainty equivalents.
The simulations use 100,000 independent random draws of \(k_I, k_M, \delta\), where \(k_I\) and \(k_M\) are informed and momentum capital, respectively, and \(\delta\) is the signal of differential fundamental value for winners minus losers. \(k_I\) and \(k_M\) (and \(k_C\)) follow a Dirichlet distribution with concentration parameters \(3\), and \(E_k = E_{k_M} = 1/3\). \(\delta\) follows a log-normal distribution with \(\mu = -2.405\) and \(\sigma = 0.125\) implying an average \(\delta\) of 9.1% with standard deviation of 1.14%. The market clearing formation period return \(f\) is solved for each \((k_I, k_M, \delta)\) pair by iteration using different specifications for momentum traders’ beliefs \(\delta^E\): known crowding in Graphs A.1–2, rational beliefs in Graphs B.1–2, myopic beliefs in Graphs C.1–2, and optimal linear beliefs in Graphs D.1–2. The expected momentum return is then \(m = \delta - f\). The 100,000 values of \((\delta, m)\) in each simulation run are ranked into 100 equally populated bins according to the horizontal-axis variable, and the graphs represent the averages for the indicated variables within these bins.
Graph A.1 of Figure 1 presents an identity relation between the mean of informed investors’ valuation spread $\delta$ and momentum investors’ expectation of it $\delta^E$. This confirms that prices fully reveal private information in the base case. Graph A.2 of Figure 1 shows that the model does not embed any tail risk in momentum returns absent crowding. In particular, there is no random draw of market conditions that yields negative expected momentum returns.

### B. Rational Beliefs

Graphs B.1 and B.2 of Figure 1 and the second column of Table 1 present the rational case. From Graph B.1 of Figure 1, mean beliefs $\delta^E$ map identically into the mean $\delta$ underlying those beliefs, consistent with rational expectations. However, the dispersion of inferences (vertical axis) is narrower than in Graph A.1, indicating that momentum investors cannot infer $\delta$ as precisely as when crowd size is known. Graph B.2 of Figure 1 indicates that even in the highest bin for $\delta^E$ momentum investors do not systematically overshoot fundamental value and generate a negative expected momentum return. From Panel A of Table 1, expected momentum returns exhibit no negative skewness, excess kurtosis, or incremental volatility, just as in the base case. From Panel B of Table 1, realized momentum returns and profitability are only slightly lower than in the base case. Overall, these results provide our main theoretical result, summarized as.

**Result 1.** When momentum investors rationally condition on the momentum portfolio price to infer crowd size, unanticipated crowding does not generate momentum tail risks.

### C. Myopic Beliefs

Graph C.1 of Figure 1 indicates a strongly concave relation between beliefs $\delta^E$ and fundamental value $\delta$ when momentum investors hold myopic beliefs. In particular, when the randomly drawn market conditions generate beliefs of a high momentum return, those beliefs systematically and grossly overstate the corresponding signal of informed investors. From Graph C.2 of Figure 1, this generates an expected momentum return $m$ on the order of $-400\%$ in the highest beliefs bin. From the third column of Table 1, momentum returns exhibit substantial excess volatility and kurtosis with extreme negative skewness. We summarize this as

**Result 2.** When momentum investors myopically employ a linear strategy, making no effort to infer crowd size from the momentum portfolio’s price, unanticipated crowding can lead to extreme tail risk in momentum returns.

Contrasting Results 1 and 2 makes it clear that unanticipated crowding can generate momentum tail risk to an essentially unbounded degree, if momentum investors employ myopic strategies. Yet, when momentum strategies are based on rational expectations, crowding-induced tail risk is completely avoided. Thus, predictions of crowding-induced tail risk depend crucially on how the momentum crowd acts when tail risk is high. If unanticipated crowding does (does not) account for momentum tail risk, then we ought to observe an elevated (reduced) crowd size.
when tail risk is high. Before turning to our empirical analysis of this matter, we consider one more simulation (as in Stein (2009)) for completeness.

D. Optimal Linear Beliefs

In this setting momentum investors base their demands on linear beliefs \( \delta^E = \lambda^{-1} f \) as in the myopic case. However, rather than completely ignoring crowding effects, investors choose a value for \( \lambda^{-1} \) between 1 (which implies momentum demands are zero for all \( f \)) and the completely myopic case of 1.5 \((= (E_k M + E_k I)^{-1})\), where \( E_k M = E_k I = 1/3 \) to yield the highest average realized utility from equation (2). We use a grid search to find that value to be \( \lambda^{-1} = 1.12 \).

From Graph D.1 of Figure 1, fundamental value \( \delta \) rises monotonically with beliefs \( \delta^E \), but the relation is nowhere near an identity as required under rationality. Investors still succumb to feedback effects and overstate beliefs when they are high (i.e., \( \delta^E > \delta \)), and they understate beliefs at just about all other levels. As a result, they sacrifice substantial profit relative to the rational case. For example, from column 4 of Table 1 certainty equivalent returns are around 70% lower. However, feedback effects of unanticipated crowding are greatly attenuated. Although there are instances of negative \( m \) in Graph D.2 of Figure 1, they are not extreme. The higher moments of momentum returns in Table 1 are well behaved. In short, by proportionately restricting trade, a linear momentum strategy can be made to attenuate crowding-induced tail risk, albeit in a grossly inefficient way.

IV. Empirical Section

We base our empirical analysis on quarterly holdings from the Thomson Reuters Institutional 13f database starting in the first quarter of 1980 and ending in the third quarter of 2015. Stock data are from the CRSP database using price and share adjustment factors, restricted to CRSP share codes 10 and 11 and a listing on AMEX, NYSE, or Nasdaq. The momentum return at time \( t \) is defined as the return of winners (stocks in the top 10% using NYSE cutoffs, sorting on returns from months \( t-12 \) to \( t-2 \)) minus the return of losers (stocks in the bottom 10% similarly constructed). Returns are value-weighted within each decile and taken from Kenneth French’s online data library.

A. Crowding Proxies

We construct crowding proxies by first applying an algorithm to designate institution \( i \) a momentum investor in quarter \( q \), then aggregating this designation using various weighting schemes.

1. Momentum Designation

Following Grinblatt, Titman, and Wermers (1995), we base our designation of a momentum investor on the following score:\(^{14}\)

\(^{14}\)In previous versions of the article, we also include an alternative scoring procedure based on the now standard 12–1 momentum strategy outlined in Jegadeesh and Titman (1993). The procedure is largely redundant and yields similar results so we restrict our attention to this procedure as it has precedence in the literature. The corresponding results are available upon request.
where \( r_{j,q} \) is the quarter \( q \) return on stock \( j \) and \( \omega \) is a portfolio weight with

\[
\omega_{i,j,q} = \frac{w_{i,j,q}P_{j,q-1}}{\sum_{j=1}^{J} w_{i,j,q}P_{j,q-1}} - \frac{w_{i,j,q-1}P_{j,q-1}}{\sum_{j=1}^{J} w_{i,j,q-1}P_{j,q-1}},
\]

and \( w_{i,j,q} \) indicates shares held in stock \( j \) by institution \( i \) at the end of quarter \( q \) and \( P_{j,q-1} \) is the price of stock \( j \) at the end of quarter \( q-1 \). We fix the prices in equation (11) to avoid passive changes in portfolio weights induced by returns.

A positive \( \text{SCORE} \) implies trading aligned with a momentum strategy. However, a single quarter of alignment in trading is surely a noisy indication of strategy. Thus, we use:

**Momentum designation.** Institution \( i \) is designated a momentum investor in quarter \( q \) if it has a positive \( \text{SCORE} \) from equation (10) in each quarter \( q-3 \) through \( q \). We denote this

\[
1_{\text{MOM}_i,q} = \sum_{l=0}^{3} 1_{\text{SCORE}_{i,l} > 0} = 4,
\]

where 1 is the indicator function.

Since 13f filings do not contain short positions, this definition could fail to identify a momentum institution whose long positions underweight winners and overweight losers while its short positions overweight losers. We believe this to be implausible as it requires extreme inconsistency between the momentum tilt of long and short positions and it implies large short positions. Mutual funds dominate our sample and the short side of their portfolios is typically small (Ang (2014)). Moreover, if a momentum investor buys winners and shorts losers they will still be scored a momentum investor under our procedure.

2. Measures of Momentum Investing

We conduct our analyses using 2 sets of 3 measures for crowd size (i.e., proxies for \( k_M \)): 6 in total. The 3 measures focus on the count of institutions following a momentum strategy (denoted by \( \text{CNT} \)), their assets under management (denoted by \( \text{AUM} \)), and their trading (more precisely, quarterly change in holdings) (denoted by \( \text{TRD} \)). The 2 sets differ with respect to the scope of crowding. Measures constructed at a factor level examine institutions’ crowding into a momentum factor-mimicking portfolio (no consideration of individual securities). Measures constructed at a security level first examine the crowd size in each component security of the momentum factor-mimicking portfolio, then aggregate across the portfolio.

As in Stein (2009), our theoretical analysis points to coordination among momentum investors as the key driving force behind crowding-induced tail risk in momentum returns. With perfect coordination, feedback effects from crowding are eliminated. On the one hand, it seems reasonable to conjecture that the ability to coordinate should depend on the number of momentum investors involved in the coordination. This suggests that a count-based measure of crowd size might best predict crowding effects. On the other hand, our rational-expectations theory shows how momentum investors can coordinate implicitly, via price. Thus, rational
momentum investors can avoid feedback effects irrespective of the number of competing peers. Thus, we consider a count-based measure to help distinguish these predictions.

We construct a count-based measure at the factor level using the fraction of momentum institutions in quarter $q$:

$$CNT_F_q = \frac{1}{N_q} \sum_{i=1}^{N_q} \mathbb{1}_{MOM_i,q},$$

(12)

Scaling by $N_q$, the total count of institutions in quarter $q$, makes the measure comparable across quarters. $CNT_F$ only considers overall momentum investing, but crowding effects might be more salient when momentum investors buy (or sell) the same individual stocks. This motivates an alternative stock-level measure of crowding. Thus, we define the crowd size at the individual security level and then aggregate across momentum securities using

$$CNT_S_q = \sum_{j=1}^{J} \left( \omega_{j,q} - \omega_{j,q} \right) \frac{\sum_{i=1}^{N_q} \mathbb{1}_{wi_{i,q}>0} \mathbb{1}_{MOM_i,q}}{\sum_{i=1}^{N_q} \mathbb{1}_{wi_{i,q}>0}},$$

(13)

where $\omega_{j,q}$ is the weight of security $j$ in the winner leg of the factor mimicking portfolio (relative market capitalization otherwise zero), $\omega_{j,q}$ is the corresponding weight in the loser leg, and the second term in the sum indicates the fraction of institutional holders of the security that follow a momentum strategy. A high (low) ratio indicates a crowded market for a winner (loser) security.\(^{15}\) The difference, summed across securities, yields $CNT_S$ as an aggregate measure of crowding.

While lack of coordination is key to crowding effects, the dollar magnitude of momentum investment should also play an important role as it directly ties to supply and demand conditions. Thus we also construct proxies for $k_M$ weighting by assets under management, and by the dollar volume of momentum trade. To do so, we first construct the following 5 variables by institution-quarter:\(^{16}\)

$$HOLD_{i,q} = \sum_{j=1}^{J} w_{i,j,q} P_{j,q} \mathbb{1}_{t_{j,q}=1}, \quad \text{WHOLD}_{i,q} = \sum_{j=1}^{J} w_{i,j,q} P_{j,q} \mathbb{1}_{t_{j,q}=-1},$$

$$LHOLD_{i,q} = \sum_{j=1}^{J} w_{i,j,q} P_{j,q} \mathbb{1}_{t_{j,q}=-1}, \quad \text{WTRD}_{i,q} = \sum_{j=1}^{J} (w_{i,j,q} - w_{i,j,q-1}) P_{j,q-1} \mathbb{1}_{t_{j,q}=1}, \quad \text{LTRD}_{i,q} = \sum_{j=1}^{J} (w_{i,j,q} - w_{i,j,q-1}) P_{j,q-1} \mathbb{1}_{t_{j,q}=-1},$$

where $t_{j,q} = \pm 1$ indicates a winner or loser security as in the model ($t_{j,q} = 0$ if not an extreme decile of past returns). We define

$$AUM_F_q = \frac{\sum_{i=1}^{N_q} HOLD_{i,q} \mathbb{1}_{MOM_i,q}}{\sum_{i=1}^{N_q} HOLD_{i,q}},$$

(14)

\(^{15}\)Because these fractions can take on extreme values at the individual security level, we winsorize at the $1\%$ and $99\%$ level.

\(^{16}\)Again, these variables winsorize at the $1\%$ and $99\%$ level.
Since these measures reference aggregate momentum capital, we denote them factor-level measures. \( \text{AUM}_F \) is essentially \( \text{CNT}_F \) weighted by institution size, whereas \( \text{TRD}_F \) weights by the dollar volume of momentum trading (quarterly change in holdings) separately in the winner and loser portfolios.

We also construct the security-level measures

\[
\text{AUM}_S = \sum_{j=1}^{J} \left( \bar{\omega}_{j,q} - \omega_{j,q} \right) \frac{\sum_{i=1}^{N_q} w_{i,j,q} P_{i,j,q} \mathbb{1}_{\text{MOM}_{i,q}}}{\sum_{i=1}^{N_q} w_{i,j,q} P_{i,j,q}},
\]

\[
\text{TRD}_S = \sum_{j=1}^{J} \left( \bar{\omega}_{j,q} - \omega_{j,q} \right) \frac{\sum_{i=1}^{N_q} \left( w_{i,j,q} - w_{i,j,q-1} \right) P_{i,j,q-1} \mathbb{1}_{\text{MOM}_{i,q}}}{\sum_{i=1}^{N_q} w_{i,j,q} P_{i,j,q}}.
\]

These are again analogs to \( \text{CNT}_S \) using weights equal to either the dollars allocated to the momentum security, \( \text{AUM}_S \), or the dollar trading in that security, \( \text{TRD}_S \). In all 6 cases, we consider both levels (generically referenced as \( \text{CROWD}_q \)) and changes (generically referenced as \( \Delta \text{CROWD}_q \)) to capture anticipated and unanticipated components. We use a GARCH(1,1) specification of expected volatility in the time series of crowding to capture uncertainty, referenced as \( \text{CROWD}_{EVOL} \).

One final comment on count versus capital-based measures. There is a close analogy in microstructure considerations of the impact of trading on prices (Jones, Kaul, and Lipson (1994)), and more general considerations of institutional trading’s impact on prices as in Sias, Starks, and Titman (2006) and Edelen, Ince, and Kadlec (2016). In both settings, it turns out that count-based measures provide a more effective proxy than capital-based measures. Hence, even though capital-based measures are closer to supply and demand conditions, count-based measures have a priori precedence and are perhaps more closely tied to coordination.

### B. Descriptive Statistics

Table 2 provides summary statistics for the 13f data in Panel A and the 6 momentum proxies in Panel B. For the purpose of Panel A of Table 2 only, we define a consistent momentum investor as any institution that scores a momentum quarter as in equation (10) in at least two-thirds of available quarters. (We do not use this momentum trader definition in our later empirical analysis because it is forward looking.) From Panel A, 16% (986/6,360) of institutions are classified as consistent momentum investors. On average, these institutions have higher turnover (26% compared to 20%); manage more assets (1.7 billion vs. 1.5 billion); and hold more stocks (181 vs. 136) than their counterparts.

17Again, fractions winsorize at the 1% and 99% level.
18Thus \( \text{CROWD} \) either collectively refers to all variants (e.g., \( \text{AUM}, \text{TRD}, \text{CNT} \) crossed with \( _F \) and \( _S \)), or to a specific variant if so noted (as in the tables).
From Panel B of Table 2, 10.8% of institutions are designated momentum investors ($\mathbb{1}_{\text{MOM}_i} = 1$) in the typical quarter (CNT-factor measure) and 14.5% of institutional capital is held by momentum investors (AUM-factor measure). Both measures are highly persistent (83% and 77%, respectively). For the typical momentum stock only 4.3% of institutional holders are classified as momentum investors (CNT-security measure), but 7.3% of the aggregate institutional investment in the stock is held by momentum investors (AUM-security measure). These security-level measures are slightly less persistent than their factor-level counterparts (62% and 69%, respectively). The TRD measures indicate that momentum investors trade about 3.4% of the institutional capital traded in the typical momentum stock (using TRD-security) or the momentum portfolio (3.5% using TRD-factor). Because most crowding variables show strong persistence, we estimate volatility with a GARCH(1,1) specification (Bollerslev (1986)) using residuals from an AR(1) regression of quarterly crowding observations.

Table 3 summarizes regressions of momentum returns using the Fama and French (1993) 3-factor model (abbreviated FF3), and a dynamic version of the same model (dynamic FF3 or DFF3). The dynamic model is motivated by the evidence in Grundy and Martin (2001) of time-varying risk exposure in the momentum portfolio. It includes regressors with an interactive indicator variable for a positive prior-year factor return. Note that the dynamic model provides a substantial improvement in adjusted $R^2$ over the traditional Fama and French model. Also note that the

| Panel A. Institutions | Mean | Med | Std. Dev. | Mean | Med | Std. Dev. | Mean | Med | Std. Dev. |
|-----------------------|------|-----|-----------|------|-----|-----------|------|-----|-----------|
| #Qtrs of data         | 37.8 | 28.0| 31.8      | 32.5 | 20.5| 30.9      | 38.8 | 29.0| 31.9      |
| #Qtrs missing         | 3.9  | 1.0 | 9.9       | 3.9  | 0.0 | 10.0      | 3.9  | 1.0 | 9.9       |
| #Stocks held          | 143.2| 62.9| 275.5     | 180.6| 87.8| 275.3     | 136.4| 58.3| 275.0     |
| Assets mgd            | 15.2 | 2.0 | 102.4     | 16.8 | 2.0 | 74.3      | 14.9 | 2.0 | 106.8     |
| Turnover              | 0.21 | 0.16| 0.17      | 0.26 | 0.21| 0.18      | 0.20 | 0.15| 0.16      |
| #Institutions         | 6,360|     |           | 986  |     |           | 5,374|     |           |

| Panel B. Crowding Variables | Mean | Std. Dev. | AR(1) | Mean | Std. Dev. | AR(1) | Mean | Std. Dev. | AR(1) |
|----------------------------|------|-----------|-------|------|-----------|-------|------|-----------|-------|
| Factor Level               |      |           |       |      |           |       |      |           |       |
| ΔCROWD                     | 0.000| 0.035     | 0.025 | 0.000| 0.019     | −0.439| 0.000| 0.017     | 0.109 |
| CROWD                      | 0.145| 0.052     | 0.770 | 0.035| 0.020     | 0.518 | 0.108| 0.029     | 0.833 |
| CROWD_EVOL                 | 0.033| 0.003     | 0.819 | 0.017| 0.002     | 0.859 | 0.015| 0.002     | 0.977 |
| Security Level             |      |           |       |      |           |       |      |           |       |
| ΔCROWD                     | 0.000| 0.039     | −0.144| 0.000| 0.021     | −0.328| 0.000| 0.025     | −0.103|
| CROWD                      | 0.073| 0.050     | 0.692 | 0.034| 0.020     | 0.456 | 0.043| 0.029     | 0.623 |
| CROWD_EVOL                 | 0.034| 0.011     | 0.947 | 0.018| 0.003     | 0.329 | 0.020| 0.007     | 0.984 |

Table 2
Descriptive Statistics

In Panels A and B of Table 2, the indicated variable is computed by institution (i.e., 13f filer) and then summarized across institutions. Qtrs, med, std. dev., and mgd refer to quarters, median, standard deviation, and managed, respectively. Assets are in units of $100 million and turnover is quarterly. Momentum investors are those institutions whose trading aligns with past returns at least 2/3 of the time. ΔCROWD and CROWD refer to the AUM, TRD, or CNT measures as indicated in the column header, either at the factor level or security level as defined in Section IV.D.1. CROWD_EVOL is the estimate of volatility from a GARCH(1,1) model.
Grundy and Martin (2001) argument applies similarly to all 3 Fama and French factors and 2 out of 3 interactive terms are significant. Also notice from the moments of momentum returns reported previously in Table 1 that momentum has substantial crash risk (high excess kurtosis with pronounced left-skewness) in our sample (which includes the momentum crash of Mar. to May 2009).

Panel A of Table 4 shows the persistence of a momentum $\text{SCORE}_{i,q}$ and a momentum designation, $\text{1}_{\text{MOM}_{i,q}}$. First note that $\text{SCORE}_{i,q}$ has a transition probability of 0.54 at both 1 and 4 quarter horizons, implying a 19% greater likelihood of a positive momentum score 4 quarters ahead than the unconditional probability of 0.45.

| Panel A. Institutions’ Type | Probabilities | Likelihood |
|-----------------------------|---------------|------------|
| $\text{SCORE}_{i,q} = 1$    | $q+1$ 0.54    | $q+1$ 1.20 |
| $\text{SM}_{i,q} = 1$       | $q+4$ 0.65    | $q+4$ 1.42 |

| Panel B. Institutions’ Trading Probabilities | Likelihood |
|---------------------------------------------|------------|
| $\text{SCORE}_{i,q} = 1$                   | $q$ 0.68   |
| $\text{SM}_{i,q} = 1$                      | $q$ 0.78   |

| Panel C. Stock Returns | $q+1$ | $q+4$ |
|------------------------|-------|-------|
| Win                    | 0.56  | 0.16  |
| Mid                    | 0.08  | 0.12  |
| Los                    | 0.02  | 0.17  |

Table 3 contains the factor exposures of quarterly momentum returns on the Fama–French 3-factor model (FF3) and a dynamic extension in which the 3 factors are interacted with dummies for positive past annual factor returns (DFF3). Alphas are monthly and t-statistics (in parentheses) use White (1980) standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| Factor Model |
|--------------|
| FF3          | 0.016*** |
| (4.39)       |
| DFF3         | 0.014*** |
| (4.26)       |

| Alpha | Mkt | SMB | HML | Dmkt | DSMB | DHML | Adj. $R^2$ |
|-------|-----|-----|-----|------|------|------|------------|
| FF3   | 0.016*** | 0.35** | 0.48** | 0.59** | 0.35** | 0.59** | 0.45       |
| (4.39) | 1.98 | 2.06 | 2.06 |
| DFF3  | 0.014*** | 0.85*** | 0.68*** | 0.95*** | 0.81*** | 0.48 | 1.02** |
| (4.26) | 2.93 | 2.71 | 2.68 | 2.06 | 2.14 |
An institution’s momentum designation $1_{\text{MOM}_{i,q}}$ persists 4 quarters ahead with probability 0.34, which is 3.32 times the 0.10 unconditional probability reported in the table.\footnote{The 10% figure presented here differs from the 10.8% figure in Table 2 because the latter is a pooled mean, rather than a steady-state probability (estimated from the quarterly transition matrix).}

In any given quarter, some institutions trade with and some against momentum (from Panel A of Table 4, the unconditional mean $\text{SCORE}_{i,q} = 0.45$).\footnote{This is less than the 59% estimate that Grinblatt, Titman, and Wermers (1995) provide for mutual funds. The difference probably reflects that our data set includes hedge funds which are contrarians on average (Grinblatt, Jostova, Petrasek, and Philipov (2016)).} A possible concern is that institutions can be classified as momentum investors even if none of them trades on relative strength signals. An investor acting on signals uncorrelated with past returns has a 50% chance of a momentum score in any given quarter. Yet, only deliberate momentum investors acting on a relative strength signal can create feedback effects and the resulting tail risk. Accidental momentum investors who trade independently of (but coincident with) past returns do not generate feedback. This highlights the importance of using a measure such as $1_{\text{MOM}_{i,q}}$ that identifies institutions that consistently follow a momentum strategy. From Table 4, 10% of all institution-quarters indicate a momentum strategy (i.e., the institution has traded in line with past returns for each of 4 consecutive quarters). An investor who trades uncorrelated with past returns has an expected $1_{\text{MOM}_{i,q}}$ of $0.5^4 = 6.25\%$. Hence, the group of observed momentum investors is indeed higher than what chance alone would predict, suggesting a subset of institutional investors deliberately follows the momentum strategy. Interestingly, as institutions as a whole approximately hold the market portfolio (Lewellen (2011)), this also suggests some institutions have a contrarian bias, as in the setup of our model.

Panel B of Table 4 evaluates predictability of trading in the stocks comprising the $12-1$ momentum factor mimicking portfolio used for momentum returns. Specifically, let $\text{MOM\_BUY}_{i,q}$ denote an indicator for

\begin{equation}
\sum_{j=1}^{J} (\omega_{i,j,q} - \omega_{i,j,q-1}) 1_{j,q} > 0,
\end{equation}

where, as before, $1_{j,q} = +1 (-1)$ when the $12-1$ past-return of stock $j$ is in the top (bottom) decile ($1_{j,q} = 0$ otherwise). $\text{MOM\_BUY}_{i,q}$ identifies investor $i$ as a net buyer of momentum stocks in quarter $q$. From Panel B, a momentum designation in quarter $q$ predicts $\text{MOM\_BUY}_{i,q+4}$ with probability 0.69. This is substantially higher than the unconditional probability (an untabulated 0.4862), as seen with the $q+4$ likelihood ratio of 1.42. It is also substantially higher than the predictability using $\text{SCORE}_{i,q}$ (a likelihood ratio of 1.15). This shows that a consistent pattern of trading on relative strength over 4 consecutive quarters (i.e., $1_{\text{MOM}_{i,q}}$) improves the identification of future momentum trading.

Table 4 also documents the rapidly changing composition of the momentum portfolio. Winners have a 56% chance of remaining winners the following quarter, but at 4 quarters the probability is only 16%, which is actually less than the 23% chance of becoming a loser. Persistence is higher with losers, with 31% retaining that classification after 4 quarters.
C. Crowding and Momentum Conditional Expected Returns

Table 5 shows the results of predictive regressions of momentum returns on the various crowding measures. In all regressions the return on the momentum portfolio is dated \( q + 1 \). In Panel A, we include as control regressors the dynamic Fama–French benchmark factors (see Table 3). Because the results in Panel A (with return benchmarking) are broadly consistent with the results in Panel B (without such controls), we focus our discussion on Panel A. In all regressions we include realized volatility of momentum returns as a control, computed from squared daily momentum returns in quarter \( q \), which Barroso and Santa-Clara (2015) show strongly predicts (negatively) momentum returns.\(^{21}\) The regression sample for momentum returns begins in the third quarter of 1981 and ends in the 4th quarter of 2015 to account for the 6 quarters of data required to compute all regressors.

We find that both \( \text{CROWD}_{q-1} \) and \( \Delta \text{CROWD}_q \) measures consistently and significantly negatively predict momentum returns. This supports the idea that the information not yet incorporated into prices from trading is decreasing in crowd

\[
\begin{array}{l}
\text{Panel A. Dynamic FF3 Model} \\
\Delta \text{CROWD}_q & -0.21^{***} & -0.34^* & -0.33^* & -0.07 & -0.41^{**} & -0.04 \\
(2.64) & (-1.94) & (-1.84) & (-0.95) & (-2.05) & (-0.31) \\
\text{CROWD}_{q-2} & -0.24^{***} & -0.34^* & -0.58^{***} & -0.18^{***} & -0.36^{**} & -0.26^{**} \\
(4.32) & (-1.87) & (-4.35) & (-3.00) & (-2.39) & (-2.52) \\
\text{CROWD}_\text{EVOL}_q & 3.06^* & 2.30 & 6.60^{***} & 0.19 & 1.58 & 0.20 \\
(2.47) & (1.31) & (3.75) & (0.75) & (1.08) & (0.56) \\
\text{Realized vol. of Mom rets.} & -0.27^{***} & -0.28^{**} & -0.25^{**} & -0.29^{**} & -0.28^{**} & -0.28^{**} \\
(-2.62) & (-2.54) & (-2.21) & (-2.45) & (-2.63) & (-2.30) \\
\text{Adj. } R^2 & 40.7\% & 31.8\% & 37.7\% & 32.6\% & 34.0\% & 31.7\% \\
\end{array}
\]

\[
\begin{array}{l}
\text{Panel B. No Risk Controls} \\
\Delta \text{CROWD}_q & -0.19^* & -0.33 & -0.29 & -0.08 & -0.44^* & -0.07 \\
(-1.94) & (-1.51) & (-1.36) & (-1.18) & (-1.69) & (-0.62) \\
\text{CROWD}_{q-2} & -0.23^{***} & -0.44^{**} & -0.50^{***} & -0.18^{***} & -0.41^{**} & -0.26^{**} \\
(-3.83) & (-2.10) & (-3.39) & (-2.79) & (-1.96) & (-2.48) \\
\text{CROWD}_\text{EVOL}_q & 2.79^* & 2.21 & 4.55^{**} & 0.01 & 0.25 & -0.06 \\
(1.83) & (1.06) & (2.27) & (0.03) & (0.14) & (-0.16) \\
\text{Realized vol. of Mom rets.} & -0.29 & -0.31^* & -0.30 & -0.33^* & -0.27 & -0.32^* \\
(-1.61) & (-1.75) & (-1.56) & (-1.77) & (-1.51) & (-1.69) \\
\text{Adj. } R^2 & 16.6\% & 9.0\% & 12.0\% & 9.7\% & 10.2\% & 8.7\% \\
\end{array}
\]

\(^{21}\)In unreported results we also controlled for the bear market states proposed by Cooper, Gutierrez, and Hameed (2004). Using this control in our sample period did not change our results.
size. It also demonstrates that our measures have power to detect crowding effects on the first moment of momentum returns.

Table 5 confirms the Barroso and Santa-Clara (2015) result on lag volatility of momentum returns even with the anticipated volatility of crowding CROWD_EVOL included as a regressor. Thus, Barroso and Santa-Clara’s (2015) result does not appear to be related to crowding uncertainty. Indeed, if anything crowding uncertainty appears to positively predict momentum returns, but this result is not robust across proxies.

D. Crowding and Tail Risk in Momentum Returns

This section considers tail risk in momentum returns. We first conduct a probit analysis of tail probabilities. We then use a sorting procedure based on lagged crowding measures.

Table 6 presents the probit analysis of tail probabilities to assess the link between crowding and negative skewness in momentum returns. In particular, we examine the conditional probability of a momentum return in the \( p \)th percentile of the unconditional distribution, where \( p \) is either 5% or 10%. Note that the mean dependency documented in Table 5 implies that crowding predicts a leftward shift in the conditional distribution of momentum returns. Thus, even with no effect on higher moments, crowding is expected to increase these tail probabilities. To address this, we use a Wald test applied to a bivariate probit analysis that considers the increase in left-tail probability relative to the decrease in right-tail probability. Our null hypothesis is that crowding fattens the left tail of momentum returns only because it shifts the entire distribution (including the mean) leftward, with no elevation in negative skew.

Panel A (B) of Table 6 considers 5% (10%) tails of the unconditional distribution of momentum returns. The more extreme 5% tail is arguably more relevant in identifying a momentum “crash,” but the 10% tail provides more data. Across Panels A and B of Table 6 the crowd measure (levels or changes) is associated with an increase in tail probability in 22 of 24 cases. The increase is never statistically reliable using the 5% tail (Panel A), but it is statistically reliable in 4 out of 12 specifications using the 10% tail (Panel B). Nevertheless, the \( p \) values (in square brackets) for the difference in left versus right tail effect are far from significant in every case. Thus, we find no evidence that crowding increases tail risk.

Figure 2 plots the time series of our crowding measures. Because the academic discovery of momentum can be attributed to either Levy (1967) or Jegadeesh and Titman (1993), it may not be surprising that we observe no increase in crowding after 1993. This result is also consistent with Grinblatt, Titman, and Wermers (1995) who find evidence of pervasive momentum investing in a sample of 155 mutual funds over the 1975–1984 sample period, a time interval set entirely before the publication of the seminal study of Jegadeesh and Titman (1993). We also notice that some of our crowding variables have a statistically significant

\[ ^{22}\text{We discuss in the context of Figure IA.3 in the Supplementary Material that this pattern is consistent with our model.} \]
time trend, but on average more than 85% of their variation is not explained by the trend.23

The measures indicate that the momentum strategy was indeed crowded during the Internet bubble. Piazzesi and Schneider (2009) find similar evidence of increased trend-following behavior during the “housing bubble” of 2007–2009. On the other hand, no striking pattern is discernible before or during the major momentum crash of 2009. If anything, momentum investing by 13f institutions seems to have retracted prior to that crash.

Baltzer, Jank, and Smajlbegovic (2019) find that institutional selling of loser stocks peaked in Germany during the Great Recession just before the 2009 momentum crash. This is consistent with the momentum strategy being crowded at the time, suggesting a causality that our results appear to contradict. But an important difference to keep in mind is that our study only considers institutions that appear to
table 6

| Level of Analysis | Factor | Security |
|-------------------|--------|----------|
| Measure of Crowding | AUM | TRD | CNT | AUM | TRD | CNT |
| **Panel A. Predicting the 5% Left Tail** | | | | | | |
| ΔCROWD_q | 8.4 | 12.3 | 19.2 | –1.4 | 11.8 | 3.8 |
| (1.49) | (1.15) | (1.17) | (–0.21) | (1.03) | (0.28) |
| [0.35] | [0.92] | [0.60] | [0.22] | [0.20] | [0.90] |
| CROWD_q-1 | 7.2 | 14.4 | 24.5* | 4.9 | 26.4 | 22.1 |
| (1.55) | (1.00) | (1.79) | (0.77) | (1.39) | (1.33) |
| [0.86] | [0.81] | [0.98] | [0.98] | [0.53] | [0.46] |
| CROWD_EVOL-q | –1.4 | 43.2 | –213.3 | –11.8 | –221.3 | –91.4 |
| (–0.02) | (0.41) | (–1.09) | (–0.42) | (–1.30) | (–1.15) |
| [0.29] | [0.43] | [0.48] | [0.17] | [0.05]* | [0.11] |
| Realized vol. of Mom rets. | 10.1*** | 9.9*** | 10.8*** | 9.9*** | 12.3*** | 9.9*** |
| (3.22) | (3.18) | (3.10) | (2.92) | (2.87) | (2.94) |
| [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** |
| **Panel B. Predicting the 10% Left Tail** | | | | | | |
| ΔCROWD_q | 11.7** | 6.7 | 16.5 | 0.4 | 12.5 | –4.9 |
| (2.40) | (0.71) | (1.32) | (0.07) | (1.36) | (–0.61) |
| [0.25] | [0.57] | [0.91] | [0.58] | [0.66] | [0.68] |
| CROWD_q-1 | 10.4*** | 15.4 | 21.8* | 6.9 | 26.9** | 9.5 |
| (2.68) | (1.25) | (2.22) | (1.47) | (2.04) | (1.18) |
| [0.35] | [0.66] | [0.93] | [0.98] | [0.46] | [0.96] |
| CROWD_EVOL-q | –11.3 | 20.7 | –187.7 | –14.1 | –65.7 | –25.1 |
| (–0.17) | (0.23) | (–1.35) | (–0.65) | (–0.84) | (–0.72) |
| [0.14] | [0.30] | [0.92] | [0.74] | [0.73] | [0.57] |
| Realized vol. of Mom rets. | 11.5*** | 11.6*** | 11.6*** | 11.4*** | 11.8*** | 10.8*** |
| (3.96) | (3.60) | (3.78) | (3.65) | (3.28) | (3.60) |
| [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** | [0.00]*** |

23 In unreported results, we also found that controlling for a time trend does not materially change any of our inferences.
consistently trade on the momentum signal as part of a deliberate strategy. Their study considers the trading of all institutions, including those that sell losers for reasons other than reaction to past returns (e.g., a correlation between financial-crisis losers and contractual constraints on institutional holdings). The latter does not generate feedback effects as in the crowding models of Stein (2009) or this article.

While the notion of tail risk surely involves pronounced left skewness, to be meaningful tail risk must also be accompanied by high volatility and excess kurtosis. In Table 7, we examine all 3 higher moments of momentum returns by sorting calendar quarters based on lagged crowding. We include a sort based on lagged realized volatility of momentum returns for comparison.

The evidence in Table 7 does not support crowding as a source of tail risk in momentum returns. Across the 3 moments and 12 specifications of CROWD and ΔCROWD, we find only 1 instance of a significant relation consistent with crowding-induced tail risk. By contrast, we find 9 instances of a significant relation consistent with momentum investors avoiding momentum tail risk (i.e., crowding measure correlated with lower volatility, more positive skewness, and lower kurtosis).

Contrast these results with the last column, where we condition on lagged volatility in momentum returns. Here, we see statistically reliable prediction of negative tail risk in all moments. This evidence is consistent with Barroso and Santa-Clara (2015) who find that a volatility-managed momentum strategy has much smaller crash risk than original momentum. This contrast between predictability of crash risk using return volatility and predictability using direct measures of crowding (particularly the contrast in direction of predictability) suggests that many momentum investors incorporate tail-risk predictability into their strategy.

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24 A large kurtosis combined with left skewness is much more meaningful if volatility is also high. A low volatility directly reduces the denominator in these quantities inflating their values.

25 We find significantly more negative skewness using the change in AUM measure at the security level; \( t \)-statistic \(-2.28\).
This would be consistent with the rational beliefs case of our model, which in turn suggests (as in Result 1) that feedback effects from crowding do not explain the tendency for high lag volatility to predict crashes. Note that tail-risk avoidance is seen most prominently in count-based (CNT) measures of crowding. Indeed, estimates using our capital-based measures (AUM and TRD) are almost always statistically indistinguishable from zero whereas CNT based measures point to tail-risk avoidance in 8 of 12 instances. This suggests that tail-risk avoidance takes the form of marginal momentum investors pulling away from the strategy in volatile environments.

We agree with much of the literature that it is tempting to interpret the predictive power of volatility for momentum returns as indirect evidence of crowding effects. Indeed, our study was originally motivated from just this perspective. However, a careful examination of this crowding hypothesis, from both a theoretical perspective based on rational beliefs and from an empirical perspective using

(e.g., via lag return volatility). This would be consistent with the rational beliefs case of our model, which in turn suggests (as in Result 1) that feedback effects from crowding do not explain the tendency for high lag volatility to predict crashes.

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E. Crowding and the Volatility of Momentum Returns

If volatility clustering in momentum returns derives from crowding rather than factors exogenous to momentum investors’ actions, then we should find that momentum volatility is positively predicted by measures of crowding. To examine this, Table 8 presents predictive regressions for realized volatility of momentum returns computed from raw and risk-adjusted (dynamic FF3) daily returns over the quarter.

Consistent with the preceding results in the literature, Table 8 finds that lagged realized volatility has strong predictive power for subsequent volatility, with t-statistics ranging between 8 and 12 across regressions. However, we find no evidence that crowding positively predicts elevated return volatility. Indeed, the relation is significantly negative in many cases. This result suggests that the expectation of momentum-strategy risk affects institutions’ willingness to participate in the strategy. Note that this interpretation implies that forward-looking
institutions observe a wider information set than just lagged volatility in momentum returns, which we have controlled for.

The explanatory power of crowding measures in Table 8 pales in comparison to that of lagged realized volatility. This is perhaps not surprising, as lag dependent variables capture all persistent characteristics of the setting. Moreover, lag volatility is estimated using daily data whereas crowding measures are based on holdings data observed at a quarterly frequency so the precision of estimates differs greatly. What the crowding measures have going for them is that they are explicit economic measures brought to bear on the data from theory. Lag dependent variables offer little economic insight beyond persistence. We believe that this fact makes up for the shortcoming in predictive power.

F. Determinants of Crowding

Table 9 presents regressions of crowding measures $\text{CROWD}_q$ on lagged 1-year momentum returns (denoted $\text{1YR\_RET}$) and 1-year momentum-return volatility (denoted $\text{1YR\_VOL}$) computed from daily observations. Crowding is significantly negatively related to volatility lagged 1 quarter, using 5 out of the 6 proxies considered. Combining inferences from Tables 8 and 9, we conclude that reductions in crowding seem to anticipate high future volatility in momentum returns including but not limited to a quick response to past volatility.

Chabot, Ghysels, and Jagannathan (2014) use a comprehensive sample period of 140 years to show that momentum crash risk increases after periods of good recent momentum returns. Piazzesi and Schneider (2009) use survey data to study momentum investing in the U.S. housing market and find a substantial increase in the number of momentum investors toward the end of the housing boom. Taken together, these studies suggest that good past returns in momentum draw investors to the strategy and increase its crash risk. Table 9 shows that 1-year returns indeed predict positively crowding in momentum, consistent with such a mechanism. However, higher past 1-year momentum returns do not predict higher crash risk

| Level of Analysis | Factor | Security |
|-------------------|--------|----------|
| Measure of Crowding | AUM | TRD | CNT | AUM | TRD | CNT |
| $\text{1YR\_RET}_q$ | 0.72** | 0.25*** | 0.41*** | 0.29 | 0.24*** | 0.17 |
| | (2.57) | (3.40) | (2.69) | (1.32) | (2.62) | (1.34) |
| $\text{1YR\_RET}_{q,s}$ | 0.92*** | 0.40*** | 0.52** | 0.35 | 0.27*** | 0.21 |
| | (3.22) | (3.93) | (2.94) | (1.29) | (3.08) | (1.34) |
| $\text{1YR\_VOL}_q$ | $-0.28^*$ | $-0.20^*$ | $-0.36^*$ | $-0.39^*$ | $-0.08$ | $-0.18^*$ |
| | ($-1.94$) | ($-3.31$) | ($-4.50$) | ($-2.46$) | ($-1.34$) | ($-2.09$) |
| $\text{1YR\_VOL}_{q,s}$ | 0.41* | 0.07 | 0.18** | $-0.10$ | 0.02 | 0.08 |
| | (1.90) | (1.34) | (2.33) | ($-0.68$) | (0.41) | (1.22) |
| Adj. $R^2$ | 10.9% | 20.1% | 19.1% | 12.9% | 10.6% | 2.2% |

TABLE 9
Momentum Factor Returns as a Determinant of Crowding

Each column in Table 9 represents a predictive regression of a different crowding measure on lag momentum returns ($\text{1YR\_RET}$) and lag momentum realized volatility ($\text{1YR\_VOL}$) computed using daily momentum returns. Intercepts are not tabulated. The t-statistics (in parentheses) are computed with Newey and West (1987) standard errors with 3 lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
in our sample.\textsuperscript{26} Hence, we are unable to relate our evidence of a dependence of crowding on past returns to the results in these papers’ linking past returns to future crash risk.

Cooper, Gutierrez, and Hameed (2004) show that momentum returns are stronger in bull markets. However, in unreported results, we find that momentum crowding is not related to lagged market states after controlling for lagged momentum returns and volatility. Thus, the well-documented predictive ability of market states for momentum returns does not seem to stem from crowding in the strategy.

G. Comparison with Return-Based Measures of Crowding

Lou and Polk (2013) propose a proxy for crowding defined as comomentum, a measure of abnormal co-movement of stocks in the momentum portfolio. In support of this proposition, they document a positive relation between comomentum and aggregate institutional ownership of the winners’ portfolio. Huang (2022) argues that the momentum gap, defined as the cross sectional dispersion of formation period returns, also proxies for crowding. He supports this by showing that it is related to the difference in institutional ownership for winner versus loser portfolios. Both studies find that the indirect, returns-based proxies for crowding negatively relate to momentum returns. Finally, volatility in momentum could also be hypothesized to arise from investor crowding, potentially representing a third returns-based proxy.

We have already seen that the relation between volatility and institutional crowding is more consistent with investors using past and anticipated future volatility as a signal to exit the strategy than investors causing volatility by way of their crowding. The question we address here is how other returns-based proxies relate to our direct measures of institutional crowding. We focus on the momentum gap due to its simplicity; because it is a strong predictor of risk and return for momentum; and because of its proximity to the theory.

Table 10 mirrors Table 7, except that the focus is momentum gap (denoted \textit{GAP}) and momentum gap orthogonalized to our crowding measures (generically denoted \textit{GAP}⊥). If momentum gap’s predictability stems from institutional crowding then orthogonalizing it should attenuate its predictability. In each column, we rank all months in our sample into terciles according to the sorting variable listed in the column heading, as of the preceding quarter. In the first column the ranking variable is the momentum gap. Consistent with Huang (2022), we find that a high momentum gap forecasts significantly higher volatility, negative skewness, and excess kurtosis. That is, momentum gap forecasts tail risk.

In the remainder of Table 10, we sort into terciles based on the momentum gap orthogonalized to each of our 6 proxies for institutional crowding, and to 2 additional variables: \textit{ΔMOM INST} from Huang (2022), defined as the percentage difference in aggregate institutional ownership between past winners and losers; and \textit{WIN INST} from Lou and Polk (2013), defined as the aggregate institutional

\textsuperscript{26}In unreported results, we found no significant relation between past 1-year momentum returns and crashes in probit regressions controlling for momentum’s volatility.
ownership of the winner decile.\textsuperscript{27} $\text{GAP}^{-}$ retains substantially all of the predictive power for tail risk of momentum gap itself (column 1). We conclude that the momentum gap is a strong predictor of momentum tail risk for reasons unrelated to institutions’ crowding in the strategy.

We also orthogonalize $\text{GAP}$ to the volatility control used in many of our preceding empirical exercises. Since $\text{GAP}$ is a measure of (cross sectional) dispersion in returns, it should closely relate to our time-series measure of volatility (indeed, the correlation is 0.73). However, $\text{GAP}^{-}$ remains a reliable predictor of future volatility: predicted volatility averages 35.6% following periods of high $\text{GAP}^{-}$ compared to 21.0% following periods of low $\text{GAP}^{-}$. The t-statistic for the difference is 3.2. However, predicted skewness and predicted kurtosis is no longer reliably different for high versus low periods of $\text{GAP}^{-}$.

V. Conclusion

We provide a model of crowding with momentum investors who attempt to infer informed investors’ private signals from prices. The model is similar to Stein (2009) setting, but our analysis differs in its exploration of and emphasis on rational

\textsuperscript{27}The $\text{WIN}_{\text{INST}}$ measure is subject to 2 concerns. First, it shows a strong time trend as the asset management industry grows over the sample implying that momentum is mechanically more crowded over time. Yet institutions as a whole approximately hold the market (Lewellen (2011)) so institutional holdings of losers must show a similar increase over time. Second, it is a measure based on holdings and therefore has high inertia.
arbitrageur beliefs. Our primary result is that predictions of destabilizing effects from unanticipated crowding require a myopic, linear specification of beliefs in which momentum investors do not adequately account for the potential destabilizing effect of crowding on prices. With rational (generally nonlinear) beliefs, the potential destabilizing effects of crowding are internalized into demands. This mitigates feedback effects that would otherwise lead to destabilized prices and results in stable momentum returns. In short, our theory shows that crowding is not a viable explanation for momentum crashes in general, but that crowding with myopic momentum investors can provide that prediction.

Our empirical contribution is 2-fold. First, we directly examine proxies for momentum investing by institutional investors, in contrast to much of the literature that focuses on indirect inferences of crowding from return covariances or volatility. Second, we directly examine the implications of optimal versus myopic beliefs, documenting a generally inverse relation between momentum investing and future tail risk in momentum returns.

Across the empirical analyses, we consistently find evidence of crash-avoidance behavior rather than destabilizing feedback trading. Consistent with our theory under rational beliefs, we find no evidence that crowding by momentum investors deteriorates the higher moments of momentum returns (i.e., causes crashes), despite a clear impact on the first moment of returns. We do find that past volatility in momentum returns identifies crashes, as in prior studies. But we also find that momentum investors both control for this result as well as condition on other sources to anticipate and back away from periods of instability.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109021000624.

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