Crowding and Factor Returns

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Abstract

This paper documents that crowding by market participants affects the expected return to popular factor strategies such as value, momentum, and carry. Using data published by the CFTC for commodity futures markets, we construct a direct measure of factor strategy crowding that is based on the aggregate positioning of market participants. We show that this crowding measure has a strong negative predictive impact on expected factor strategy returns. Historical factor strategy returns are accumulated primarily during periods of low crowding. We link variation in our crowding measure to macroeconomic fundamentals and suggest that the reduction of factor strategy returns is related to variation in the cost of arbitrage capital.

Keywords: Commodity futures, factor returns, crowding, momentum, value, basis.

1. Introduction

The past four decades have witnessed a proliferation of studies that examine the cross-sectional relationship between pre-determined characteristic variables and subsequent security returns. Based on this research, academics and practitioners have developed a multitude of factor strategies, many of which have been implemented in the practice of investment management. While compelling historical, back-tested returns have undoubtedly contributed to the growing popularity of factor investing, several recent academic papers suggest that the profitability of such strategies have declined in comparison to their historical track records (e.g., Chordia et al. (2014) and McLean and Pontiff (2016)).[1]

There are two primary explanations for this attenuation, which are not mutually exclusive. The first is that many factor premiums, when first reported, may be biased upwards due to data snooping (Lo and MacKinlay (1990)) and therefore overstate the true returns that investors can expect out of sample. Under this explanation, the lower out-of-sample returns earned by investors are the reflection of a reversion to the mean of the underlying distribution of factor premiums. McClean and Pontiff (2016) have documented the decline in out-of-sample returns of factor strategies since first publication, and Harvey et al. (2016) propose a multiple testing approach for establishing the statistical significance of factor premiums.

The second explanation, which we explore in this paper, is that the increasing popularity of factor investing reduces returns when strategies become more crowded over time. Absent

[1] Specific examples include Fama and French (2020), Israel et al. (2020), Maloney and Moskowitz (2020), who examine the low returns to value strategies in equity markets over the past decade, and Bhardwaj, Janardanan, and Rouwenhorst (2019), who document low returns to momentum strategies in commodity futures markets over the past decade.

a natural clientele for factor "shorts" in the market, investors bid up prices of assets that provide high factor exposure, depressing those with low exposure, thereby gradually decreasing expected factor returns through the accumulation of investor flows. The increased investor allocations to factor strategies (Amenc et al. (2014), Clarke et al. (2016), Ghayur et al. (2016)) have occurred during a period of improving market liquidity (Chordia et al. (2011)) and a decline of interest rates, both of which have lowered the cost of deploying arbitrage capital.

While the crowding hypothesis of return attenuation has intuitive appeal, it has received little direct support in the finance literature. The premise of crowding is that concentrated positioning by investors lowers subsequent returns. The complication of empirically establishing the impact of crowding is that systematic data on aggregate positions are typically unavailable in practice. Several studies have documented the relationship between *flows* (changes in positions) by *subsets* of investors and short-term expected returns, but few of these studies have focused on the aggregate longer-term return impact of persistent aggregate positions shifts. As an alternative to measuring positions, recent empirical research has suggested return-based measures of crowding (Baltas (2019), Lou and Polk (2020)).

In this study, we provide direct evidence that crowding influences subsequent returns in commodity futures markets using weekly investor positions data that is collected by the Commodity Futures Trading Commission (CFTC). We choose to study the market for commodity futures for three reasons. First, factor strategies have historically enjoyed popularity among commodity futures investors, and the profitability of factor strategies (such as carry and momentum) in commodity futures markets has been widely documented in the literature (Pirrong (2005), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Moskowitz, Ooi and Pederson (2012), Koijen et. al. (2018)). Second, the CFTC data on aggregate trader positions allows for the construction of holdings-based measures of crowding that covers the entire population of market participants. Because the CFTC reports trader positions on a weekly basis, the holdings can be observed at a frequency that is likely to be relevant for the rebalancing periodicity of factor strategies. Third, the trader classifications by the CFTC are likely to be informative of the crowding of factors strategies. Moskowitz, Ooi, and Pederson (2012) and Kang, Rouwenhorst, and Tang (2020) show that the positions of trader groups defined by the CFTC vary distinctly with factor return realizations, in particular momentum. The commodity futures market therefore provides a unique laboratory to develop a holdings-based measure of factor crowding and to trace the impact of variation in strategy crowding on subsequent strategy profitability.

We define our measure of crowding as the "excess speculative pressure," measured as the deviation of non-commercial traders' positions from their long-term average in commodity futures markets, scaled by open interest. While this crowding metric is defined at the individual commodity level, it can be naturally aggregated to the (portfolio) strategy level. The starting point of our empirical analysis is to apply this measure in the context of a momentum strategy, which is the most common factor strategy followed by Commodity Trading Advisors (CTAs).

Our first major empirical finding is that commodity level crowding predicts subsequent commodity futures excess returns. Next, we find that commodity level crowding metrics, when aggregated to the portfolio level, help to predict factor strategy returns. For example, the returns to momentum investing are highest during months when the strategy is least crowded, and lowest when it is most crowded according to our definition. Specifically, our crowding measure helps to explain why the returns to commodity momentum investment have been low during the last several years of our sample. Our crowding metric is able to predict momentum returns after controlling for other factors that have been documented in the literature to predict commodity futures excess returns, such as past excess returns and recent investor flows into the market. A one standard deviation increase in our crowding metric decreases the return of the momentum factor by around 8% annualized, which is comparable in magnitude to the unconditional long-term average factor risk premium.

Next, we use our measure of crowding to analyse the returns to basis (carry) and value strategies. Similar to momentum, periods of low crowding account for most of the profits to a carry strategy, and the return to investing in a commodity futures value strategy depends on whether the investment is made during periods of low or high crowding.

Our findings are robust to different return specifications, such as the choice of contract tenor, alternate factor construction methods, as well as alternate definitions of crowding. Furthermore, we also present parallel set of results using the Disaggregated Commitment of Traders (DCOT) report published by the CFTC, and find similar strategy return predictability based on crowding by traders categorized as money managers.

Finally, we examine the determinants of crowding, i.e., factors that influence the propensity of investors to crowd their trades. We find that crowding is primarily the result of performance chasing by investors: across all factor strategies good past performance leads to an increase in crowding of that strategy. However, consistent with the limits-to-arbitrage literature, we find that the willingness of speculators to bet on factors decreases when the funding cost (proxied by the TED spread or the repo rate) are high and when commodity-level volatility increases.[2]

Our study contributes to the literature as follows. First, we propose a simple metric of crowding at the individual commodity level that can be easily aggregated to a strategy-level measure of crowding. Second, our measure of crowding is directly based on the holdings of market participants instead of return correlations (e.g. Baltas (2019), Lou and Polk (2020)). Third, we show that our crowding measure predicts factor returns: an increase in factor crowding is followed by significantly lower average factor returns. Finally, we explore the macroeconomic determinants that affect the propensity of investors to crowd their positions and link this to variation in the cost of arbitrage capital.

Our study is related to the demand-based asset pricing literature, which suggests that high demand for a security tends to lower its subsequent returns. This has been documented in several asset markets; equity options (Garleanu, Pedersen, and Poteshman (2009)), individual lottery-like stocks (Bali et al. (2017), government bonds (Greenwood and Vayanos (2014)), and commodity futures (Kang, Rouwenhorst and Tang (2020). Our study extends this literature by showing that the negative relationship between investor demand and subsequent returns is an important determinant of time variation in the returns to popular factor strategies.

The remainder of our paper is organized as follows. Section 2 describes the data and empirical methodology used in this study. Section 3 introduces our crowding measure and provides preliminary evidence of how crowding affects expected returns at the individual commodity level. Section 4 shows our main result that crowding can predict factor returns

[2] Hanson and Sunderam (2014) show that the short-interest in the loser portfolio of an equity momentum strategy significantly decreases when the TED spread widens and the volatility increases.

in commodity futures markets. Section 5 examines the determinants of the factor crowding. Section 6 summarizes the results of a set of robustness checks. Section 7 concludes the paper.

2. Data

The study combines data on commodity futures prices and trader positions. Positions data for trader positions is obtained from the Commitment of Trader (COT) report, which is published weekly by the Commodity Futures Trading Committee (CFTC) on the Tuesday of each week. Our sample covers 26 commodities that are traded on North American exchanges (CBOT, CME, and NYMEX) from January 2, 1993 to December 31, 2019.

In the COT dataset, the CFTC reports the aggregate long and short positions of commodity futures traders, that are classified as either commercials, non-commercials, or non-reportables. According to CFTC Regulation 17 CFR 1.3(z), a trader will be categorized as “commercial” if she uses futures contracts for hedging purposes. Reportable traders (i.e., those who are large enough to meet the CFTC reporting threshold) that do not meet the definition of “commercial” are classified as “non-commercial”. In addition to the COT positions, we will conduct robustness checks that are based on the Disaggregated COT (DCOT) reports which are published by the CFTC since 2006. The DCOT reports use a finer partitioning of trader classifications: producers/merchants/processors/users, money managers, swap dealers, other reportables, and non-reportables.

Commodity futures price data are obtained from Commodity System Inc. Because CFTC data measure positions of traders by the end of trading on the Tuesday of each week, we calculate the weekly excess returns (Tuesday-Tuesday) to match the measurement of these positions. Excess returns are calculated as:

$$R_{i,t} = \frac{F_i(t,T) - F_i(t-1,T)}{F_i(t-1,T)} \tag{1}$$

where $F_i(t,T)$ is the price at time t for the first nearby contract for commodity i maturing on date T.[3]

3. A holdings-based measure of crowding.

To our knowledge there exists no widely accepted definition of crowding in the literature. Intuitively, crowding suggests a concentration of positions that deviates from the "normal" distribution of asset holdings across investors. A precise definition of crowding would require a model to specify the "normal" distribution of asset holdings. For example, the Capital Asset Pricing Model predicts that all investors hold risky assets in proportion to their weights in the market portfolio. A natural definition of crowding in the CAPM could be based on deviations from the market portfolio weights by subsets of investors, much like the "active share" definition proposed by Cremers and Pettajisto (2009). Asset pricing models that incorporate investor heterogeneity would likely suggest different baselines to gauge crowding, but all models would share the important feature that concentration of positions by one subset of investors would require underweighting of those positions by others in the market.

Because futures are in zero net supply, standard asset pricing models do not provide

[3] For the week with Tuesday prior to or on the 7th calendar day of the month, the first-nearby contract is defined as the closest to maturity contract. For the week with Tuesday after the 7th calendar day, the first-nearby contract is defined as the contract expiring subsequent to the current calendar month. If the 7th calendar day is not a business day, the next business day is thus used as the cut-off date. The contracts selected following this strategy generally takes futures prices in the most liquid futures contract. Popular commodity indexes follow a similar strategy in selecting contracts in the index to ensure good liquidity for the futures contracts. For example, SPGSCI rolls its position from the 5th business day to the 9th business day. Here we use the 7th business day in each month as the cut-off date for the reason of simplicity and being parsimonious in our empirical methodology.

predictions about the distribution of futures holdings. Our crowding measure is therefore motivated by two empirical stylized facts documented in the literature about the balance between hedging and speculative positions in commodity futures markets. First, in most markets average hedging pressure is positive: the size of short hedging positions on average exceeds the size of long hedging (Bessembinder (1982), DeRoon and Nijman (2000)), with speculative capital absorbing this structural hedging imbalance. Second, short-term fluctuations in hedging pressure are primarily driven by speculative investment flows, whereas the low-frequency component of hedging pressure reflects the demand for price protection by hedgers (Kang et al (2020)). Building on these findings, we decompose the level of net speculative positioning into a "normal", low-frequency component that is needed to meet the structural imbalance in the hedging demand for commodity futures, and a component that is driven by the shorter-horizon investment motives of speculators that are independent of insurance provision to hedgers. This second component forms the foundation for our measure of crowding.

We calculate speculative pressure for the i^{th} commodity at the end of week *t* as the non-commercial net long position, NC_t^i, standardized by open interest:

$$NC_t^i = \frac{NonCommercialLong_t^i - NonCommercialShort_t^i}{OpenInterest_t^i}. \tag{2}$$

The "normal" level of speculative pressure that is needed to meet the structural imbalance in hedging demand is calculated as:

$$NCbar_t^i = \frac{1}{52}\sum_{k=1}^{52} NC_{t-k}^i. \tag{3}$$

Speculative crowding in commodity *i* at time *t*, is the speculative pressure in excess of the level that is needed to match the structural hedging demands by commercial traders:

$$Crowding_t^i = NC_t^i - NCbar_t^i. \tag{4}$$

Our crowding metric at the commodity level attempts to capture the active investment decisions by non-commercials.[4] In the next section we will show that it is straightforward to aggregate individual commodity crowding to the portfolio or strategy level. In the remainder of this section we will provide some summary statistics for our crowding metric and present preliminary evidence that our measure of crowding helps to predict excess returns in the cross-section of individual commodities.

3.1 Summary statistics on positions and crowding.

Panel A of Table 1 provides summary statistics for excess returns, speculative net positions, and crowding for each of the 26 commodities markets in our sample. Over our sample period, commodity futures excess returns average around 3% per annum, with a standard deviation about 27.5%. In 24 markets the net-long speculative position is on average positive, mirroring the positive hedging pressure of commercial traders. More importantly, the standard deviation of speculative net long position is large (around 15%), indicating that there is substantial time-series variation in these positions. It suggests that speculators trade for reasons other than to merely accommodate commercial hedging demands. The final columns provide summary statistics for our crowding measure. By construction, the mean and median values of commodity level crowding are close to zero. The time-series standard deviation of crowding averages about 12% across commodities. This and the average interquartile range of -8.3% to 8.2% both point to substantial variation

[4] The speculative crowding measure is defined as the net long position of non-commercial traders minus its own past 52-week moving average. Kang et al (2020) suggest that hedging demand for commodity futures can be measured as the past 52-week moving average of the commercials net short position. We present robustness checks that our results are similar if we define crowding based on deviations of the average of the non-commercial positions. Finally, note that in constructing the crowding metric, we remove any time trends in speculative pressure.

in commodity level crowding. Consistent with the findings in Kang et al (2020), speculative positions show substantial short-term variation that is independent from accommodating the hedging demands of commercial traders, which are unlikely to vary substantially at the weekly horizon.

3.2 Preliminary evidence on the importance of crowding.

Before examining whether crowding plays an important role in predicting the return of factor strategies, we want to test whether our crowding measure has predictive power for risk premiums at the individual commodity level. We examine the impact of crowding on subsequent excess returns by running weekly univariate cross-sectional Fama-MacBeth regressions of individual commodity futures excess returns on lagged (i.e. beginning of week) levels of crowding. In a separate set of regressions, we control for variables that have been shown in the literature to predict futures risk premiums in the cross-section: the futures basis, the change of net commercial long positions (Q), the smoothed component of hedging pressure (SHP), lagged one week returns and past one-year returns.[5] The results are in Table 2. Individual commodity crowding has a strong predictive power on the subsequent returns in both univariate and multivariate specifications with controls. We present separate results for next-week excess returns and returns in weeks 2-4 to measure the persistence of the return impact of crowding. In all specifications, high levels of crowding significantly predict low subsequent excess futures returns. The point estimates and the statistical significance of the impact of crowding are stable to the inclusion of control variables, which capture a

[5] Kang, Rouwenhorst, and Tang (2020) show that the change of non-commercial's net long position (Q), the smoothing hedging pressure (SHP) can predict the subsequent commodity futures returns. Szymanowska et al (2014) documents that basis has predictive power on commodity returns. Miffre and Rallis (2007) show that the past commodities returns up to one year have predictive power on future returns.

substantial amount of independent return variation. This suggests that our crowding measure exerts a significant influence on returns that is separate from variables documented in the literature.

The economic impact of crowding is significant as well: a one standard deviation increase in crowding reduces subsequent week commodity returns by 13 bps. Over the next three weeks (2-4), the estimated impact is 20bp, which adds up to a combined return impact of 34 bps (or around 4% annualized) over a four-week period. To put these estimates further into perspective: they are similar in magnitude to estimates of the unconditional commodity futures market risk premium and the returns on commodity factor strategies reported in the literature (Gorton and Rouwenhorst (2006), Erb and Harvey (2006), Gorton et al.(2013)). The conclusion is that our proposed measure of crowding captures independent variation of positions on subsequent returns at the commodity level. In the next section, we explore the role of crowding in explaining the time variation in returns on factor strategies.

4. Factor crowding and factor portfolio returns.

Factor strategy crowding is a natural extension of commodity level crowding. For a long-short factor portfolio, we calculate the average of the signed crowding metrics of the individual portfolio constituents (+1 for long positions, and -1 for short positions). Factor crowding is calculated as:

$$Crowding_t^{factor} = average\left(Sign^i \times Crowding_t^i\right)$$

$$= \frac{1}{2}\left[average\left(Crowding_t^{i,long}\right) + average\left(-Crowding_t^{i,short}\right)\right]. \qquad (5)$$

4.1 Factor returns and crowding: summary statistics.

We focus on three commonly used factor trading strategies in commodity futures markets: momentum, value, and basis strategies. The momentum factor is calculated by a weekly ranking of our 26 sample commodity futures based on past one-year returns, and taking an equally-weighted long position in the top half and an equally-weighted short position in the bottom half. For our value factor, we follow Asness, Moskowitz, and Pedersen (2013), and conduct a similar sorting procedure of ranking commodities from low to high on their ratio of current nearby futures price scaled by the nearby futures prices three years ago. The basis factor portfolio is constructed by taking long positions in 13 commodities with the highest futures basis (measured as the percentage price difference between closest and next-to maturity contracts), and short positions in commodities with the lowest futures basis.[6]

Panel B of Table 1 shows the average weekly returns and standard deviations of these three factor trading strategies that are rebalanced weekly. The average factor returns are 0.152% (momentum), 0.180% (basis), and 0.043% (value) per week, or 7.9%, 9.4%, and 2.2% on an annualized basis.[7] We do not suggest that the weekly horizon is the optimal rebalancing interval for these strategies. The focus of our paper is on the time variation in these factor returns and the impact of crowding on the predictable component of this time variation. Panel C of Table 1 reports the summary statistics for crowding of the factor portfolios. Average crowding levels are close to zero for value and basis strategies, but positive for momentum. This is consistent with the findings in Kang et al (2020) that

[6] In Appendix Table A2, we present robustness checks for different methods to form these strategies. The main results of this paper continue to hold.

[7] Contrary to Asness, Moskowitz and Pedersen (2013) we do not find that value strategies are profitable in our sample. This can be attributed to the different sample period in their paper and a different commodity set. Our value factor earns comparable returns to theirs over the period that our samples overlap. Our findings for momentum returns are comparable as well.

speculative position changes are positively correlated with past returns. Because the momentum signal sorts on past returns, it implicitly sorts on past flows that can lead to current crowding. Interestingly, Hayashi et al (2013) suggest that high basis commodities are also likely to have experienced past price increases, but this does not show up in higher average levels of crowding for the basis strategy.

Figure 1 illustrates the evolution of the crowding of factor strategies over time. The figure shows that all strategies exhibit time variation in crowding. Momentum stands out because it exhibits an upward trend in crowding over the sample. Based on our results from commodity level crowding this would predict a reduction of momentum strategies over time. We will explore these issues in more detail in the next section.

4.2 Crowding and momentum factor returns.

In this section we examine how the profitability of factor strategies varies with the level of crowding. We start out with an analysis of momentum, and in contrast to Table 1 (which reports returns for a weekly rebalanced strategy), we will trace the evolution of momentum profits over the 13-week period following portfolio formation. The top portion of Table 3 shows that the average cumulative excess return gradually increases over time and reaches 1.28% at the end of the 13^{th} week following portfolio formation. Next, we classify calendar weeks as either high or low crowding depending on whether the level of crowding for momentum is above or below the full sample median during that week. The bottom half of Table 3 reports separate average event time returns to momentum for high crowding (C2) and low crowding weeks (C1). The table shows that conditioning on crowding spreads the excess returns to momentum.

When crowding is low, momentum is highly profitable: its post ranking return increases from 0.28% in the first week to 2.51% in week 13. All cumulative factor returns in this scenario are significant at 1% significance level. In sharp contrast, profitability to momentum is absent in periods of high crowding. At all horizons up to 13 weeks, cumulative momentum profits fluctuate around zero. The difference in the profitability of momentum strategy between the low- and high-crowding scenarios is statistically significant at all horizons. We conclude that crowding plays a key role in predicting the profitability of momentum strategies in commodity futures markets.

A potential pitfall of the analysis above, is that sorting conditional on the full sample median embeds a forward looking bias. To address this concern, we also classify crowding levels by taking deviations from its trailing three year (156-week) moving average. In Figure 2 we separately cumulate the (weekly-rebalanced) momentum factor returns in high- and low-crowding months defined this way between 1997 and 2019. The blue line in Figure 2 shows that the cumulative excess return earned during weeks of low crowding exceeds 140% over the 23-year sample period, compared to a total excess return during high crowding weeks that is below 20% (red line). These findings mirror our conclusion from Table 3, that the momentum premium accrues primarily during weeks when the factor experiences low crowding.

4.3 Predictive power of crowding and controls

It is likely that the positions that investors take when allocating to factor strategies are correlated with variables that are known to predict returns. For example, Kang et al. (2020) show that speculative inflows are correlated with contemporaneous and past returns, both of which are correlated with crowding. To isolate the influence of crowding we regress post-formation momentum factor returns on past levels of crowding with and without controls variables that have been shown in the literature to predict returns. The lagged control variables include smoothed hedging pressure (*SHP*) and the change of commercial net long positions (*Q*) at the momentum portfolio level, overall commodity market excess returns, and a dummy variable to indicate a recession. *SHP* and *Q* are calculated at the individual commodity level as in Kang et al. (2020). Similar to the construction of portfolio-level crowding, *SHP* and *Q* of the momentum portfolio are calculated as the average of the signed *SHP* and *Q* of individual commodities in the long and short legs of factor portfolio. The commodity market return is calculated as the equal-weighted portfolio return of the 26 sample commodity futures. The recession dummy follows the NBER dating of US business cycles and is equal to 1 in recessions and zero otherwise.

The first column in Table 4 illustrates the strong negative predictive power of (pre-formation) crowding at the time of factor portfolio construction on the first week (post-formation) momentum returns. The coefficient of -0.06 (t -stat = -3.99) implies that a one standard deviation change in crowding lowers the next-week momentum factor returns by 16bp. Adding controls has little impact on the size of the coefficient on crowding. Among the controls, past *Q* has a significantly negative coefficient for the one-week horizon. Buying (selling) pressure on the winners (losers) during the portfolio construction week has a separate negative impact on the first week momentum factor returns. Crowding captures cumulative speculative pressure, while *Q* measures the recent change in speculative pressure. Both matter for nearby momentum factor returns. Kang et al. (2020) find that the liquidity provision effect is strongest at the one-week horizon. This is consistent with the results in the next columns for the momentum return in week 2-4 following portfolio formation. The negative coefficient for crowding remains significant, whereas the coefficient on Q becomes insignificantly different from zero. Adding the coefficients for crowding from both regressions implies that a one-standard-deviation increase in strategy crowding on average lowers post ranking 4-week momentum returns by 70bps, which translates to about 8% annualized.

4.4 Crowding of Value and Basis Factors

This section examines the impact of crowding on the returns to value and basis strategies. We form long-short portfolios using the signals for value and basis described in Section 4.1, and trace the post-ranking excess returns for 13 weeks after portfolio formation. Table 5 reports the unconditional event-time returns as well as a breakdown of factor returns conditional on crowding levels. Results for value are in Panel A of Table 5, and basis in Panel B.

The absolute and relative profitability of the value and basis strategies matches the averages reported in Table 3 for the weekly rebalanced strategies. As in the case of momentum, conditioning on crowding levels significantly spreads the excess event time returns for both strategies. Returns are significantly higher during weeks of low crowding and lower when crowding is high. The return spread associated with crowding in value at the end of 13 weeks (−2.56%, t = −2.88) is comparable in magnitude of the spread in momentum returns, and larger than for basis factor excess returns (−1.49%, t = −2.20). For all strategies, the excess return in high crowding weeks is low in absolute terms and becomes negative for our value strategy. Stated differently, the excess return to factors strategies in commodity futures primarily accrues during weeks when crowding is low.

These findings are unchanged when we remove the forward-looking aspect from the classification of crowding scenarios. Figures 3 and 4 show that most of the positive average excess returns of the value and basis factors accrue in low crowding weeks. Low, or negative average returns, are earned during episodes of high crowding.

Table 6 presents the time series predictability regressions for value and basis factor returns, with and without controls as in Table 4. As before, the predictive power of crowding is robust to the inclusion of controls. A one-standard-deviation increase of crowding of the value (basis) factor portfolio decreases the next-week strategy return by 19 (9) bps and next four-week return by 67 (33) bps, respectively.

In the Appendix Table A1, we calculate the factor returns and crowding metrics in 5-year subsamples. In particular, we find that the momentum factor has become more crowded since 2015 and has also experienced low average returns. Unlike momentum, value and basis strategies do not exhibit a similar increase in crowding or decline in average returns.

Overall, we find that the return predictability of crowding on the value and basis factors are to our findings for the momentum factor. Average factor returns decline when strategies become crowded. Our results mirror the findings of Hanson and Sunderam (2014), who show that factor returns in equity markets decline when there is a higher amount of capital allocated to short-interest positions that aligns with factor positions.

5. The determinants of crowding

In this section we examine economic conditions that influence the intensity of strategy crowding. We consider three sets of variables. The first include proxies for funding liquidity

– the TED spread (the difference between the Eurodollar rate and the Treasury yield) and the repo rate. The second is the strategy's own lagged performance – the factor return in week t-1. The third set of possible determinants includes the volatility of commodity markets. We consider both the average individual commodity return volatility and the factor's past return volatility. Because crowding is highly persistent, we evaluate the contribution of these variables while controlling for lagged crowding levels.

All three panels of Table 7 show that lagged factor returns help to predict subsequent strategy crowding: when a factor performs well, crowding levels increase after controlling for past crowding. This empirical finding applies to all three factor strategies and is robust to the inclusion of other explanatory variables. One possibility is that it is a reflection of what happens at the individual commodity level: when a strategy does well, its (signed) constituents must have done well, leading to more subsequent crowding at the commodity level that is inherited by the strategy. It may also include a feedback mechanism, whereby an individual commodity becomes more crowded because it is included in a well performing (or crowded) strategy.

Table 7 also shows that crowding in momentum, and to some extent in the basis strategy, loads negatively on our proxies for funding liquidity. Crowding in value responds to these proxies with the opposite sign, albeit marginally significant.

With respect to volatility, we find that the momentum factor crowding tends to decrease when the volatility in commodity futures markets increases. When volatility increases, investors may become more averse to taking momentum bets, leading to a reduction in crowding. This result weakens to some extent when the funding liquidity proxies are also included into the regression. We do not find that volatility matters for crowding of basis and value strategies.

5.1 Factor returns and commodity level crowding.

In Table 8 we explore the effect of strategy returns on commodity level crowding. In the first regression, we predict individual commodity crowding by its own lagged return, including lagged crowding and controls that are known to predict commodity returns. Not surprisingly, returns positively predicts future crowding. This is consistent with the literature on speculative capital chasing returns.[8]

In the second regression specification we predict commodity level crowding by the (position signed) returns to the factor portfolios that the commodity is a member of. For example, if the momentum factor return is positive and the commodity is long (short) in the factor portfolio, the signed return is positive (negative). In this setup, innovations in commodity level crowding are modelled as a feedback that runs through the return of factor strategies. The coefficients on all three factors are significantly positive, suggesting that the performance of factors portfolio strongly contributes to predicting crowding in individual commodities. This could be through the "own" mechanical effect of individual commodities impacting performance impacting factors, or through cross-covariances between with the performance of commodities with similar characteristics.

[8] Fung and Hsieh (1997, 2001) analyze trend following strategies by hedge funds. Bhardwaj, Gorton, and Rouwenhorst (2014) show that the returns of Commodity Trading Advisors correlate with simple momentum. Rouwenhorst and Tang (2012) show that speculative positions are positively correlated with relative returns in commodity futures markets. Moskowitz, Ooi and Pedersen (2012) document that speculators follow time-series momentum strategies in many futures markets.

In the third specification, we include the component of the individual commodity return that is orthogonal to the signed factor returns as a regressor. This is calculated as the residual of individual commodity return on the momentum, value, basis, and market factors. The regression shows that both the factor related component of the return as well as the component of the commodity return that is orthogonal to the factor have predictive power for commodity level crowding.

6. Robustness Checks

6.1 Analysis based on the DCOT data.

Our analysis theretofore is based on the CFTC COT dataset. The COT data has the advantage of a long history (starting from 1992), but is also known to aggregate positions of potentially dissimilar traders into the same category.[9] In the DCOT data commodity futures traders are classified into five groups: (i) producers / merchants / processors / users, (ii) money managers, (iii) swap dealers, (iv) other reportables and (v) non-reportables (or small investors). The first group refers to futures market participants that are often thought of as having a clear hedging motive. The second group – money managers – includes hedge funds and commodity trading advisors (CTA), which form the subset traders in the CFTC data that is most likely to follow the factor strategies that we study in this paper.

We construct an alternative version of our crowding metric based on the positions of money managers. These two crowding measures based on non-commercial positions (COT)

[9] In particular, a financial institution that hedges an over-the-counter commodity index swap with an index investor and takes long positions in the futures markets as a hedge would be classified as a commercial trader, whereas the underlying trading motive is speculative in nature. The DCOT data contains a finer breakdown of positions, including a separate category for swap dealers. The report has been published by the CFTC since 2006 June.

and positions of money managers (DCOT) turn out to be highly correlated: the correlation coefficient is 0.92 for the period during which these two samples overlap.

Panel A of Table 9 shows a similar pattern of factor return predictability by our measures of crowding constructed using the DCOT data. High crowding of positions by money managers predicts lower subsequent factor returns for all the three factors strategies, both with and without controls. Our prior results are therefore robust to alternative speculative trader definitions.

Panel B shows that past factor returns predict subsequent crowding of the momentum, value, and basis factor portfolios. This is consistent with what we find in Section 5 above. The predictive power of the of remaining variables is generally weaken, perhaps attributable to the shorted sample period for the DCOT data.

6.2 *A comparison with the return-correlation-based measures of crowding*

Lou and Polk (2020) propose an indirect measure of crowding that is based on the abnormal return correlation among stocks in the top and bottom momentum portfolios. They argue that this correlation based crowding measure is a proxy for the arbitrageur trading activity in these factor portfolios, where an elevated return correlation signals higher crowding of the factor strategy. They document that elevated return correlations predict low subsequent momentum returns.

We construct correlation-based crowding measures for our commodity futures factors in the spirit of Lou and Polk (LP measure). Due to the small cross-section of commodities relative to stocks in the LP sample, we base the construction of the LP measure on the 13-13 long-short portfolios for momentum, value and basis but otherwise follow their methodology. We then add the LP co-movement measure in our return prediction regressions in tables 4 and 6.

As shown in Table 10, including the LP's co-movement proxy has little impact on the coefficient estimates of our crowding measure in the return prediction regressions for all three factors, with the coefficients of our crowding measures remaining significant in all regression specifications. In fact, they are essentially unchanged when compared with the estimates from the regression without the LP's co-movement proxy (see Tables 4 and 6).

As for the LP co-movement proxy itself, we find that it has negative coefficients in the momentum return prediction, which is consistent with the argument with Lou and Polk (2020), but the coefficients are not statistically significant. A possible explanation is that our LP measure of crowding is noisy due to the limited cross-section of commodities.

Either way, the table underscores the importance of using direct position-based data to obtain a better understanding of the dynamics of crowding for factor returns.

6.3 Robustness Tests

We conduct several additional tests of the robustness of our main findings of the predictive power of crowding for subsequent factor returns. In the Appendix Table A2, we examine sensitivity to the term structure of futures prices, and construct factor returns using the second-nearby commodity futures contract. The table shows that our crowding measure significantly predicts subsequent factor returns that are constructed on longer dated futures contracts. In the Appendix Table A3, we evaluate the sensitivity of our results to alternative factor construction methods. More specifically, we form momentum factor portfolios by sorting on past 6-month or 9-month returns, base the value factor on the past 5-year returns, and generate the basis factor using the futures price difference between the second-nearby and third-nearby futures contracts. For all these alternative factor portfolio construction methods, we obtain broadly similar conclusions about the factor return predictability of crowding. In Appendix Table A4, we construct a crowding measure based on the number of traders instead of the numbers of contracts as reported in the COT non-commercial data. We find qualitatively similar results, with somewhat lower *t*-statistics. This perhaps is not surprising. For the purpose measuring speculative price pressure, the aggregate size of the overall position is more relevant than the number of traders. In Appendix Table A5, we construct a measure of crowding that measures speculative pressure in excess of the level required to meet the structural hedging demand of commercial traders. As in Kang et al (2020), this structural demand is calculated as smoothed hedging pressure, which is a past 52-week moving average of the commercials net short position. So instead of using the average of the non-commercial positions as a baseline, we use commercial positions as a benchmark. The table shows that our finding of factor return predictability is robust for this alternative measure of crowding. In Appendix Table A6, we repeat the individual-commodity level return-prediction regression by using the DCOT data, and find that the crowding measure based on the DCOT money managers' position data significantly predicts individual commodity returns over the next 1 to 4 weeks. These results further confirm that money managers constitute the primary category of traders who engage in speculative crowding.

7. Conclusion

This paper shows that crowding affects the expected return to popular factor strategies such as value, momentum, and carry. Using data published by the CFTC for commodity futures markets, we construct a direct measure of factor strategy crowding that is based on the aggregate positioning of market participants.

We find that our crowding measure negatively predicts subsequent factor returns – factor expected returns tend to be lower when these strategies becomes more crowded. The impact of crowding is economically significant. We show that during our sample period from 1993 to 2019, the factor premiums are accumulated primarily during periods of low crowding.

Finally, we establish the link between the variation in our measure of crowding and macroeconomic fundamentals, as well as the strategy's own past returns. Our findings suggest that crowding and the reduction of factor strategy returns are related to a decline in the cost of arbitrage capital.

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Table 1: Summary Statistics

This table summarizes the variables used in this paper. Panel A shows the returns (in annualized percentage numbers) and speculator's net-long positions for the 26 commodities in the sample. Panel B shows the summary statistics of weekly returns of the momentum, value, and basis factor returns in commodity futures markets. Note for the momentum, value, and basis factor portfolios, their long and short legs include 13 commodities in each, that is, a half-long and half-short approach. The portfolio formation periods for momentum and value strategies are 1 year and 3 years, respectively; the holding period of all three factor strategies are one week. Panel C lists the summary statistics for the crowding measures for the momentum, value, and basis factor portfolios, which are constructed based on the definition described in equations (2) and (3) of the paper. The sample period is from January 1993 to December 2019.

Panel A: Annualized Excess Returns, Commercial Net-long Position and Crowding by Commodity

	Annualized Return (%)		Speculators' Net Position		Crowding				
	mean	standard deviation	mean	standard deviation	mean	median	standard deviation	25%	75%
Wheat	-5.196	28.676	-0.038	12.350	-0.002	-0.008	0.101	-0.066	0.066
KansasWheat	-0.055	27.516	8.827	12.997	-0.001	-0.003	0.107	-0.079	0.068
MinnWheat	6.431	25.690	5.241	13.601	-0.004	-0.009	0.093	-0.063	0.051
Corn	-2.559	25.865	8.878	11.756	-0.002	-0.004	0.107	-0.075	0.072
Oat	7.923	33.143	14.477	13.967	0.007	0.003	0.114	-0.068	0.087
Soybean	6.851	22.677	10.170	13.848	-0.004	0.005	0.124	-0.089	0.085
SoybeanOil	0.414	22.910	7.145	13.167	0.000	0.005	0.119	-0.080	0.084
SoybeanMeal	13.207	26.245	10.579	12.031	-0.001	-0.007	0.110	-0.078	0.075
RoughRice	-4.521	26.083	0.525	18.126	0.002	0.003	0.135	-0.096	0.100
Oil	6.731	32.803	7.351	9.080	0.005	0.003	0.049	-0.026	0.037
HeatingOil	6.697	30.622	3.026	6.293	0.000	0.002	0.056	-0.038	0.036
NaturalGas	-11.982	44.947	-5.888	9.742	-0.003	-0.006	0.060	-0.047	0.039
Cotton	-0.115	27.727	5.721	21.330	0.000	-0.001	0.183	-0.126	0.122
OrangeJuice	2.601	32.193	12.036	22.391	-0.008	-0.012	0.182	-0.132	0.127
Lumber	-4.506	32.280	4.078	17.813	-0.003	-0.013	0.166	-0.134	0.110
Cocoa	4.578	29.464	8.496	15.020	-0.002	0.000	0.106	-0.076	0.078
Sugar	6.759	31.504	9.352	14.100	-0.003	-0.004	0.133	-0.082	0.082
Coffee	2.398	37.098	5.199	15.384	-0.004	-0.010	0.137	-0.104	0.087

Platinum	6.503	21.579	37.453	21.313	-0.001	0.008	0.178	-0.114	0.124
Palladium	15.818	32.713	31.869	25.455	0.004	0.013	0.153	-0.084	0.093
Silver	6.876	28.060	22.984	14.073	-0.001	-0.007	0.126	-0.085	0.081
Copper	7.047	23.880	2.929	15.640	-0.002	-0.009	0.132	-0.108	0.082
Gold	4.522	15.946	17.604	23.297	0.003	-0.007	0.135	-0.083	0.087
Lean Hogs	-3.169	25.885	7.511	13.139	0.001	0.004	0.122	-0.077	0.088
Live Cattle	2.167	15.505	12.209	11.643	0.004	0.009	0.102	-0.064	0.071
Feed Cattle	2.558	15.077	11.210	13.643	0.000	-0.001	0.128	-0.091	0.091
Average	2.999	27.542	9.959	15.046	-0.001	-0.002	0.121	-0.083	0.082

Panel B: Factor Portfolio Excess Returns

Weekly Returns (%)	mean	(t-stat)	25%	75%
Momentum	0.152	(*3.325*)	-0.978	1.297
Value	0.043	(*0.849*)	-1.121	1.224
Basis	0.180	(*4.432*)	-0.852	1.224

Panel C: Factor-Portfolio Crowding

Crowding	mean	median	std	25%	75%
Momentum	0.039	0.033	0.061	-0.006	0.080
Value	-0.006	-0.003	0.050	-0.037	0.027
Basis	0.002	0.002	0.051	-0.030	0.033

Table 2: Crowding and Next Week Individual Commodity Excess Returns

The table reports the coefficient estimates of regressions of weekly futures excess returns of individual commodities on the lagged measures of crowding, with and without the inclusion of a set of lagged control variables. The crowding measure of individual commodities is constructed according to inequation (2). We run both Fama-MacBeth regressions and a panel regression. For the Fama-Macbeth regressions, we estimate aa cross-sectional return prediction regression in each week, and then report the time-series average of the coefficient estimates, with the *t*-statistics reported in parentheses below the coefficients. For the panel regression, we include both a commodity and a week fixed effect in the regression. For briefness, we omit presenting the coefficient estimates for the dummies in the regression. The standard errors for both regressions are adjusted using the Newey-West method with thirteen lags.

Dependent Variable Returns	Fama-MacBeth				Panel			
	1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.011	-0.010	-0.020	-0.017	-0.010	-0.008	-0.015	-0.012
	(*-5.19*)	(*-4.22*)	(*-3.50*)	(*-2.98*)	(*-6.24*)	(*-4.61*)	(*-3.42*)	(*-2.55*)
Q		-0.049		-0.051		-0.035		-0.032
		(*-6.22*)		(*-3.62*)		(*-7.07*)		(*-3.26*)
SHP		0.004		0.013		0.002		0.011
		(*2.69*)		(*3.47*)		(*1.39*)		(*2.27*)
Basis		0.003		0.003		-0.001		-0.004
		(*1.86*)		(*0.69*)		(*-0.42*)		(*-0.90*)
Lagged Ret		0.040		0.020		0.025		0.011
		(*4.07*)		(*1.11*)		(*3.17*)		(*0.91*)
R^2	5.1%	29.0%	5.0%	28.9%	18.9%	19.0%	18.5%	18.6%

Table 3: Momentum Factor Returns and Crowding – Portfolio Sorting Approach

This table presents average momentum factor returns by week, up to 13 weeks after the time of portfolio construction. The top half of the table reports the unconditional momentum returns; the bottom half of the table reports the momentum returns conditional on whether factor crowding is above (C2) or below (C1) the full sample median in that week. The *t*-statistics are in parentheses and are adjusted using the Newey-West method with thirteen lags.

	Crowding	Post-Formation Cumulative Excess Return to Momentum												
	in Week 0	1	2	3	4	5	6	7	8	9	10	11	12	13
		Unconditional Momentum Factor Returns												
Momentum Returns		0.15	0.28	0.39	0.50	0.61	0.70	0.82	0.90	0.99	1.05	1.14	1.21	1.28
(*t*-statistic)		(*3.32*)	(*3.04*)	(*2.90*)	(*2.93*)	(*2.88*)	(*2.87*)	(*2.95*)	(*2.91*)	(*2.88*)	(*2.82*)	(*2.84*)	(*2.80*)	(*2.78*)
		Momentum Factor Returns Conditional on Crowding												
C1 (low crowding)	-0.01	0.28	0.56	0.86	1.12	1.29	1.46	1.66	1.81	1.96	2.10	2.26	2.39	2.51
C2 (high crowding)	0.04	0.02	-0.01	-0.09	-0.12	-0.08	-0.06	-0.03	-0.01	0.00	-0.01	0.02	0.01	0.03
C2-C1	0.05	-0.26	-0.57	-0.95	-1.24	-1.38	-1.52	-1.68	-1.81	-1.97	-2.11	-2.24	-2.39	-2.49
(t-statistic)		(*-2.81*)	(*-3.32*)	(*-3.91*)	(*-4.03*)	(*-3.69*)	(*-3.51*)	(*-3.45*)	(*-3.31*)	(*-3.25*)	(*-3.18*)	(*-3.12*)	(*-3.10*)	(*-3.04*)

Table 4: Momentum Factor Returns and Crowding – Regression Analysis

The table analyses the predictability of momentum factor returns using lagged strategy crowding, with and without a set of control variables. The momentum strategy is constructed from a long 13 winners and short 13 losers formed by sorting based on past one-year excess returns. The control variables are the strategy-adjusted smooth hedging pressures (averaged spread of smooth hedging pressure between winners and losers), strategy-adjusted trading position changes (averaged spread of position changes between winners and losers), the past one-year commodity market returns, and a recession dummy. The *t*-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Portfolio Holding Horizon	1 week		2-4 weeks	
Portfolio Crowding	-0.060	-0.052	-0.186	-0.182
	(*-3.99*)	(*-3.05*)	(*-4.52*)	(*-4.02*)
Portfolio SHP		-0.006		0.000
		(*-1.00*)		(*-0.01*)
Portfolio Q		-0.078		0.007
		(*-2.60*)		(*0.15*)
Market Return		0.034		0.297
		(*0.18*)		(*0.65*)
Recession Dummy		0.000		-0.001
		(*-0.18*)		(*-0.21*)
R^2	1.1%	1.7%	3.4%	3.5%

Table 5: Value and Basis Factor Returns and Crowding – Portfolio Sorting Approach

This table presents average factor returns by week, up to 13 weeks after the time of portfolio construction. Panel A reports results for Value, panel B for Basis. The top half of each panel reports the unconditional factor returns; the bottom half of the table reports the factor returns conditional on whether factor crowding is above (C2) or below (C1) the full sample median in that week. The *t*-statistics are in parentheses and are adjusted using the Newey-West method with thirteen lags.

Panel A: Value Factor

	Crowding	Post-Formation Cumulative Average Excess Return												
	in Week 0	1	2	3	4	5	6	7	8	9	10	11	12	13
Unconditional Value Factor Returns														
Value Factor Returns		0.04	0.07	0.09	0.12	0.15	0.16	0.18	0.18	0.20	0.21	0.21	0.23	0.26
(*t*-statistic)		(*0.85*)	(*0.69*)	(*0.66*)	(*0.64*)	(*0.66*)	(*0.59*)	(*0.56*)	(*0.52*)	(*0.53*)	(*0.51*)	(*0.47*)	(*0.47*)	(*0.51*)
Average Factor Returns Conditional on Crowding														
C1 (low crowding)	-0.03	0.22	0.36	0.48	0.60	0.75	0.82	0.93	1.03	1.17	1.26	1.35	1.45	1.55
C2 (high crowding)	0.01	-0.13	-0.22	-0.29	-0.36	-0.44	-0.49	-0.57	-0.65	-0.75	-0.82	-0.91	-0.98	-1.01
C2-C1	0.04	-0.35	-0.58	-0.77	-0.96	-1.19	-1.31	-1.50	-1.68	-1.92	-2.09	-2.26	-2.43	-2.56
(*t*-statistic)		(*-3.23*)	(*-3.05*)	(*-2.87*)	(*-2.69*)	(*-2.76*)	(*-2.58*)	(*-2.58*)	(*-2.61*)	(*-2.75*)	(*-2.76*)	(*-2.81*)	(*-2.87*)	(*-2.88*)

Panel B: Basis Factor

	Crowding Measure in Week 0	Post-Formation Cumulative Average Excess Return												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Unconditional Basis Factor Returns														
Basis Factor Returns		0.14	0.26	0.37	0.51	0.63	0.74	0.92	1.12	1.31	1.47	1.65	1.84	2.03
(*t*-statistic)		(*3.26*)	(*3.02*)	(*3.07*)	(*3.22*)	(*3.25*)	(*3.29*)	(*3.62*)	(*3.99*)	(*4.30*)	(*4.53*)	(*4.80*)	(*5.10*)	(*5.39*)
Average Factor Returns Conditional on Crowding														
C1 (low crowding)	-0.02	0.26	0.49	0.71	0.89	1.06	1.20	1.36	1.59	1.84	2.09	2.34	2.58	2.78
C2 (high crowding)	0.02	0.02	0.02	0.03	0.12	0.20	0.28	0.49	0.65	0.78	0.86	0.96	1.08	1.29
C2-C1	0.04	-0.24	-0.47	-0.68	-0.77	-0.86	-0.92	-0.87	-0.94	-1.06	-1.23	-1.39	-1.50	-1.49
(*t*-statistic)		(*-2.63*)	(*-2.78*)	(*-2.88*)	(*-2.51*)	(*-2.36*)	(*-2.23*)	(*-1.90*)	(*-1.87*)	(*-1.93*)	(*-2.09*)	(*-2.22*)	(*-2.30*)	(*-2.20*)

Table 6: Value and Basis Factor Returns and Crowding – Regression Analysis

The table analyses the predictability of factor returns using lagged strategy crowding, with and without a set of control variables. The value strategy (Panel A) takes long and short positions in 13 commodities each, by sorting based on past three-year change in the log spot price. The basis strategy (Panel B) takes long and short positions in 13 commodities each, by sorting on the end of prior week futures basis. Both strategies are weekly rebalanced. The control variables are the strategy-adjusted smooth hedging pressures (averaged spread of smooth hedging pressure between winners and losers), strategy-adjusted trading position changes (averaged spread of position changes between winners and losers), the past one-year commodity market returns, and a recession dummy. The *t*-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Panel A: Value Factor

Portfolio Holding Horizon	1 week		2-4 weeks	
Portfolio Crowding	*-0.080*	*-0.074*	*-0.184*	*-0.192*
	(*-3.25*)	(*-2.89*)	(*-2.99*)	(*-3.04*)
Portfolio SHP		-0.005		-0.007
		(*-0.72*)		(*-0.35*)
Portfolio Q		-0.057		-0.011
		(*-1.62*)		(*-0.19*)
Market Return		-0.135		-0.317
		(*-0.61*)		(*-0.56*)
Recession Dummy		0.002		0.008
		(*0.67*)		(*1.27*)
R^2	1.2%	1.6%	2.1%	2.7%

Panel B: Basis Factor

Portfolio Holding Horizon	1 week		2-4 weeks	
Portfolio Crowding	-0.038	-0.034	-0.104	-0.096
	(*-2.28*)	(*-1.89*)	(*-2.36*)	(*-2.04*)
Portfolio SHP		0.006		0.014
		(*1.14*)		(*1.04*)
Portfolio Q		-0.029		-0.043
		(*-1.24*)		(*-1.13*)
Market Return		0.013		-0.029
		(*0.09*)		(*-0.07*)
Recession Dummy		0.002		0.006
		(*1.52*)		(*0.98*)
R^2	0.4%	0.8%	0.9%	1.5%

Table 7: Determinants of the Factor Portfolio Crowding

The table reports the predictive regression coefficients and R-squared of the factor crowding on lagged values of crowding, and proxies for funding cost, lagged factor returns, and measures of commodity market risk and factor risk. The funding cost proxies include the TED spread and repo rate. The commodity variance is obtained by averaging the variance of individual commodities calculated from daily futures returns from week t-4 to week t-1. The factor variance is obtained by calculating the annualized variance of the factor-strategy returns from t-52 to t-1. The *t*-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Panel A: Determinants of Momentum Factor Crowding

Crowd(t)	(1)	(2)	(3)	(4)	(5)	(6)
TED Spread(t-1)	-0.319					-0.196
	(*-4.56*)					(*-1.79*)
Repo Rate(t-1)		-0.056				-0.049
		(*-3.49*)				(*-2.58*)
Factor Returns(t-1)			0.041			0.046
			(*1.93*)			(*2.12*)
Commod Variance(t-1)				-0.013		-0.002
				(*-1.30*)		(*-0.13*)
Factor Variance(t-1)					-0.103	-0.082
					(*-1.58*)	(*-1.02*)
Crowding(t-1)	0.868	0.866	0.878	0.875	0.874	0.858
	(*59.45*)	(*62.05*)	(*63.92*)	(*62.05*)	(*60.96*)	(*58.99*)
R^2	77.11%	77.12%	77.03%	77.05%	77.01%	77.29%

Panel B: Determinants of Value Factor Portfolio Crowding

Crowd(t)	(1)	(2)	(3)	(4)	(5)	(6)
TED Spread(t-1)	0.144					0.014
	(*1.74*)					(*0.14*)
Repo Rate(t-1)		0.018				0.028
		(*1.13*)				(*1.45*)
Factor Returns(t-1)			0.1255			0.124
			(*5.32*)			(*5.23*)
Commod Variance(t-1)				0.016		0.027
				(*2.20*)		(*2.02*)
Factor Variance(t-1)					-0.004	-0.078
					(*-0.10*)	(*-1.26*)
Crowding(t-1)	0.819	0.820	0.820	0.820	0.821	0.813
	(*38.94*)	(39.68)	(*40.05*)	(*39.15*)	(*39.45*)	(*39.36*)
R^2	67.50%	67.48%	68.31%	67.48%	67.45%	68.46%

Panel C: Determinants of Basis Factor Portfolio Crowding

Crowd(t)	(1)	(2)	(3)	(4)	(5)	(6)
TedSpread(t-1)	-0.165					-0.056
	(*-1.87*)					(*-0.50*)
Repo Rate(t-1)		-0.046				-0.043
		(*-2.04*)				(*-1.66*)
Factor Returns(t-1)			0.080			0.081
			(*3.25*)			(*3.31*)
Commod Variance(t-1)				-0.006		-0.012
				(*-0.58*)		(*-0.84*)
Factor Variance(t-1)					0.076	0.054
					(*1.01*)	(*0.53*)
Crowding(t-1)	0.761	0.755	0.760	0.762	0.762	0.752
	(*37.43*)	(*37.14*)	(*38.38*)	(*37.78*)	(*38.75*)	(*36.77*)
R^2	58.11%	58.21%	58.33%	58.07%	58.07%	58.53%

Table 8: Determinants of Crowding at Individual Commodity Level

The table reports the predictive panel regression coefficients and R-squared of the crowding measure on lagged values, respectively, of various determinants including commodity returns, variance (demeaned) and basis, Q and hedging pressure for individual commodities. The commodity variance is calculated using daily futures returns in week *t*. Momentum*Sign (or Value*Sign / Basis*Sign) is the lagged momentum (or value/basis) factor return times +1 or -1 conditional on whether the specific commodity is in the long or short leg of the factor portfolio. We also decompose the individual commodity returns into factor-related and factor-unrelated component using a rolling window of 26 weeks by projecting individual commodity returns on 3 factors (momentum, basis and value). The *t*-statistics in italic is adjusted using the double clustering method.

Commodity-Level Crowding	(1)	(2)	(3)
Commodity Return	0.181		
	(*7.62*)		
Momentum*Sign		0.035	0.044
		(*3.23*)	(*3.95*)
Value*Sign		0.041	0.047
		(*2.51*)	(*2.76*)
Basis*Sign		0.049	0.06
		(*3.24*)	(*3.77*)
Factor-unrelated Return			0.179
			(*7.62*)
Controls	Yes	Yes	Yes
Lag Crowding	Yes	Yes	Yes
R^2	90.82%	90.57%	90.77%

Table 9: Crowding based on DCOT Positions of Money Managers

he table reports the results based on the crowding of money manager positions reported in the DCOT data. Panel A reports the predictive regression coefficients and R-squared of subsequent factor returns on the lagged value of crowding and control variables. Panel B reports the predictive regression coefficients and R-squared of the factor crowding measure on various determinants including funding cost proxies and past factor returns and variances. The commodity variance is obtained by averaging the variance of individual commodities calculated with daily futures returns from week t-4 to week t-1. The factor variance is obtained by calculating the annualized variance of the factor-strategy returns from t-52 to t-1. The sample period is from June 2006 to December 2019.The *t*-statistics in parentheses are adjusted using the Newey-West method with thirteen lags.

Panel A: Factor Returns and Money Manager Crowding

	Momentum				Value				Basis			
	1 week		2-4 weeks		1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.052	-0.040	-0.190	-0.192	-0.080	-0.072	-0.238	-0.208	-0.080	-0.090	-0.230	-0.238
	(*-2.18*)	(*-1.38*)	(*-3.14*)	(*-2.77*)	(*-2.51*)	(*-2.27*)	(*-3.05*)	(*-2.45*)	(*-3.11*)	(*-3.31*)	(*-2.20*)	(*-2.06*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.8%	1.3%	3.4%	4.1%	1.2%	1.9%	3.6%	6.6%	1.2%	2.2%	2.3%	3.4%

Panel B: Determinants of Factor Portfolio Crowding

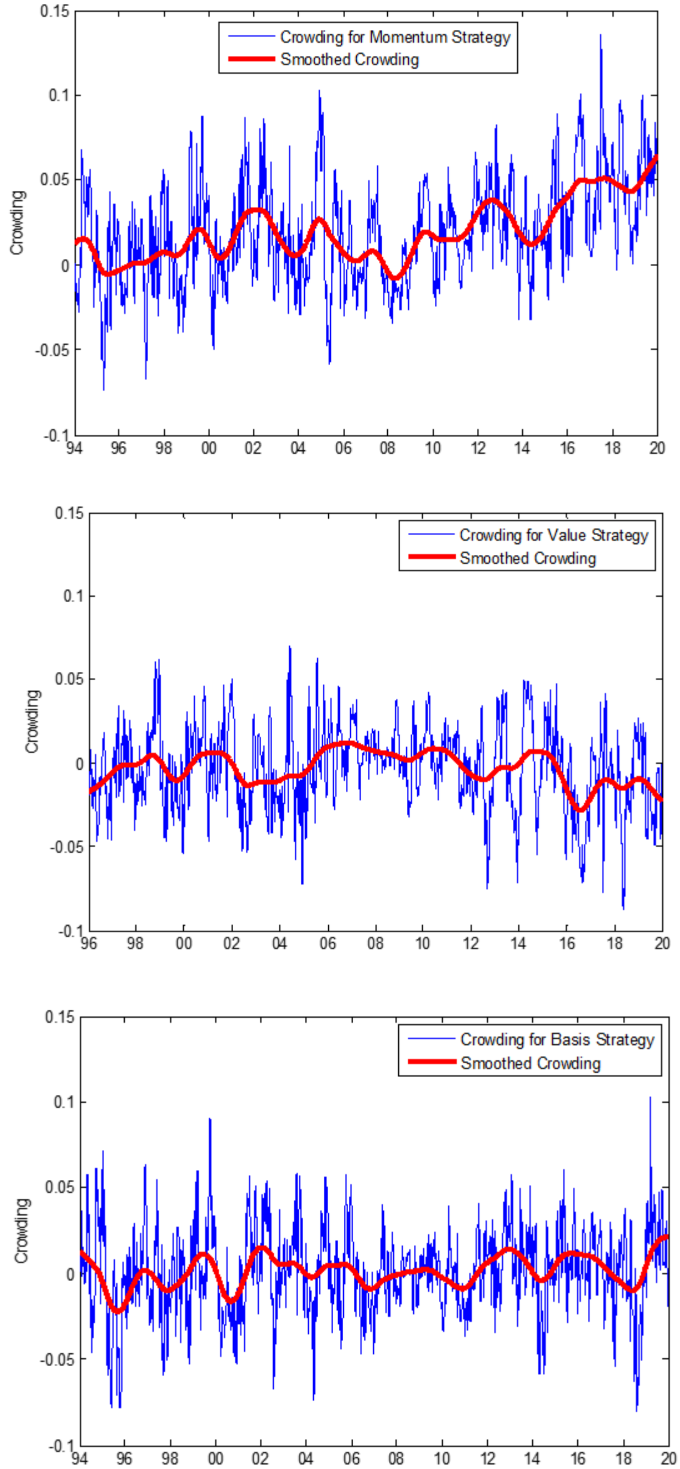
Crowd(t)	Momentum	Value	Basis
TED Spread(t-1)	-0.218	0.007	-0.129
	(*-1.66*)	(*0.06*)	(*-0.89*)
Repo Rate(t-1)	0.007	0.002	0.031
	(*0.13*)	(*0.04*)	(*0.46*)
Factor Returns(t-1)	0.046	0.104	0.127
	(*1.82*)	(*3.83*)	(*3.89*)
Commodity Variance(t-1)	-0.003	0.019	-0.007
	(*-0.18*)	(*1.16*)	(*-0.37*)
Factor Variance(t-1)	-0.005	-0.111	0.058
	(*-0.05*)	(*-1.55*)	(*0.41*)
Lag Crowding	Yes	Yes	Yes
R^2	79.56%	75.72%	58.60%

Table 10: Holding-based versus Correlation-based Measures of Crowding

In this table, we follow the spirit of Lou and Polk (2020) method to construct a correlation to proxy the crowding of a factor strategy. Specifically, we first regress commodity returns on three factors (momentum, basis and value) with a roll 26-weeks window; then we take the averaged correlation of residuals for the long leg then minus the averaged correlation for the short leg as the Lou-Polk's correlation measure. The table reports the regression coefficients and R-squared of strategy returns (%) of different subsequent holding weeks on an intercept, the lagged crowding measure and a set of lagged control variables. The three strategies are constructed from a long 13 commodities and short 13 commodities portfolio. The t-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Subsequent returns	Momentum				Value				Basis			
	1 week	2-4 weeks	1 week	2-4 weeks	1 week	2-4 weeks	1 week	2-4 weeks	1 week	2-4 weeks	1 week	2-4 weeks
Crowding			-0.051	-0.181			-0.073	-0.191			-0.038	-0.099
			(*-3.01*)	(*-4.03*)			(*-2.89*)	(*-3.03*)			(*-1.95*)	(*-1.88*)
LP Comovement Proxy	-0.014	-0.034	-0.012	-0.028	-0.015	0.025	-0.015	0.024	-0.011	-0.037	-0.014	-0.044
	(*-0.85*)	(*-0.64*)	(*-0.70*)	(*-0.55*)	(*-0.66*)	(0.36)	(*-0.69*)	(0.37)	(*-0.69*)	(*-0.77*)	(*-0.87*)	(*-0.92*)
Portfolio SHP	-0.003	0.012	-0.006	0.001	-0.003	-0.001	-0.005	-0.007	0.008	0.018	0.007	0.016
	(*-0.45*)	(0.71)	(*-0.91*)	(0.05)	(*-0.39*)	(*-0.06*)	(*-0.71*)	(*-0.36*)	(1.29)	(1.20)	(1.17)	(1.09)
Portfolio Q	-0.095	-0.054	-0.078	0.007	-0.080	-0.066	-0.058	-0.010	-0.046	-0.089	-0.034	-0.060
	(*-3.29*)	(*-1.25*)	(*-2.60*)	(0.16)	(*-2.31*)	(*-1.19*)	(*-1.65*)	(*-0.17*)	(*-1.81*)	(*-2.36*)	(*-1.31*)	(*-1.45*)
Market	0.183	0.811	0.046	0.325	-0.151	-0.411	-0.123	-0.337	0.114	0.357	0.049	0.189
	(0.96)	(1.64)	(0.24)	(0.68)	(*-0.66*)	(*-0.71*)	(*-0.55*)	(*-0.60*)	(0.72)	(0.75)	(0.31)	(0.39)
Recession Dummy	0.000	0.002	0.000	-0.001	0.001	0.006	0.001	0.008	0.003	0.008	0.003	0.008
	(0.19)	(0.32)	(*-0.22*)	(*-0.25*)	(0.39)	(1.04)	(0.63)	(1.32)	(1.51)	(1.31)	(1.60)	(1.37)
R^2	1.10%	0.80%	1.80%	3.50%	0.70%	0.60%	1.60%	2.70%	0.60%	1.20%	0.90%	1.90%

Figure 1: The Time-Series Crowding of Momentum, Value, and Basis Factor Strategies



The red curves are smoothed with HP filter, where lambda is selected to be 160000.

Figure 2: Momentum Profits Conditional on Crowding

The figure presents two momentum strategies that condition on momentum-factor crowding: For the low crowding strategy, at each week if momentum crowding is below its past-three-year's average, a momentum portfolio of long 13 winners and short 13 losers is constructed based on past one year's accumulative returns and held for 1 week, otherwise not trade. For the high crowding strategy, the same momentum portfolio is constructed only if crowding is above its past-three-year's average, and otherwise not trade.

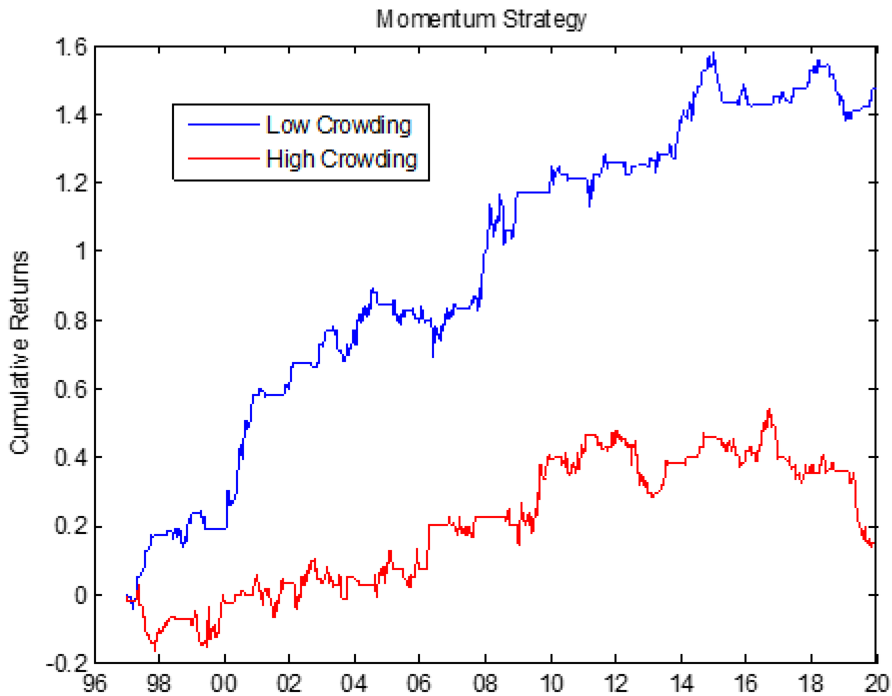


Figure 3: Value-factor Profits Conditional on Crowding

The figure presents two value strategies that condition on value-factor crowding: For the low crowding strategy, at each week if value-factor crowding is below its past-three-year's average, a value portfolio of long 13 losers and short 13 winners is constructed based on log nearby futures price difference between now and three years before and held for 1 week, otherwise not trade. For the high crowding strategy, the same value-strategy portfolio is constructed only if crowding is above its past-three-year's average, and otherwise not trade.

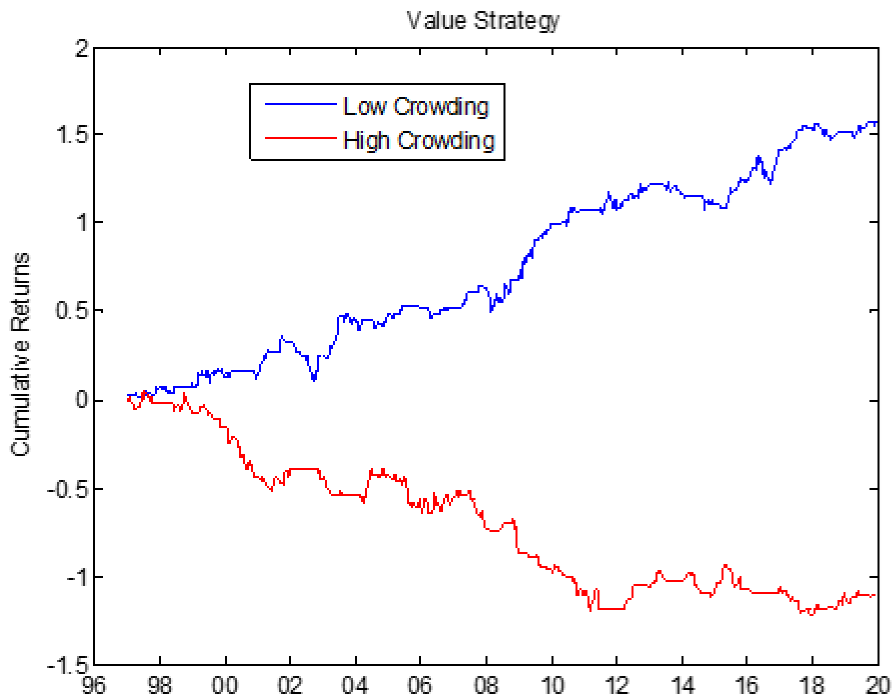
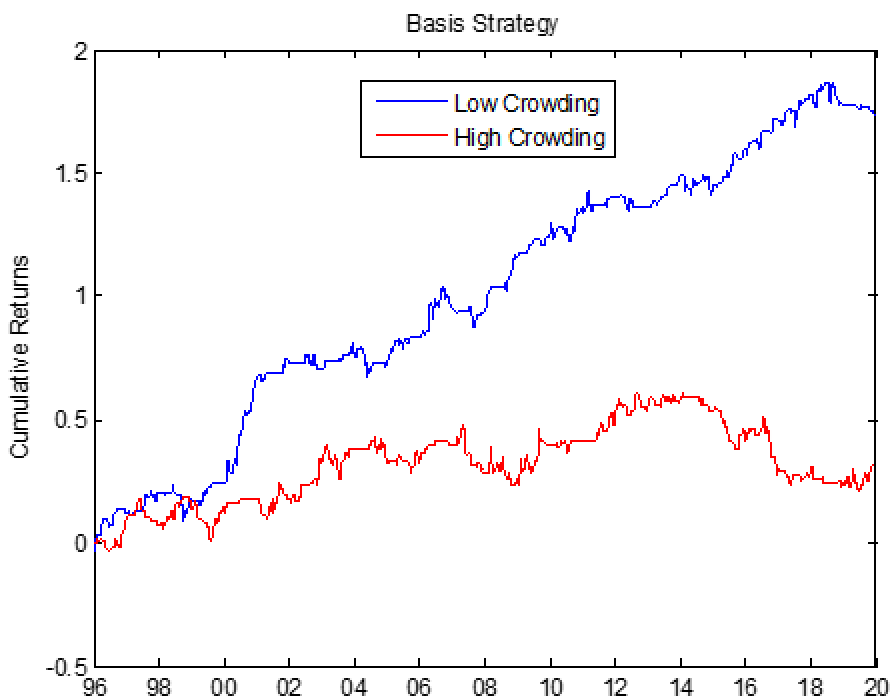


Figure 4: Basis-factor Profits Conditional on Crowding

The figure presents two basis strategies that condition basis-factor crowding For the low crowding strategy, at each week if basis-factor crowding is below its past-three-year's average, a basis-strategy portfolio of long 13 winners and short 13 losers is constructed and held for 1 week, otherwise not trade. For the high crowding strategy, the same basis-strategy portfolio is constructed only if crowding is above its past-three-year's average, and otherwise not trade.



Appendix

Table A1: Factor Returns and Crowding by Five-Year Interval

The table reports the five-years average factor returns and the crowding measure. The momentum strategy is constructed based on the past one-year futures returns. The value strategy is constructed based on three years price ratio. In all three strategies, the holding period is one week.

Panel A: Momentum Factor

	1994-1998	1999-2003	2004-2009	2010-2014	2015-2019
Weekly Returns (%)	0.222	0.258	0.243	0.157	-0.146
Crowding	0.005	0.038	0.020	0.043	0.092

Panel B: Value Factor

	1994-1998	1999-2003	2004-2009	2010-2014	2015-2019
Weekly Returns (%)	0.101	-0.044	0.049	-0.006	0.194
Crowding	0.013	-0.013	0.007	-0.001	-0.025

Panel C: Basis Factor

	1994-1998	1999-2003	2004-2009	2010-2014	2015-2019
Weekly Returns (%)	0.084	0.057	-0.060	0.033	0.043
Crowding	-0.012	-0.001	0.011	0.003	0.004

Table A2: Robustness Test Based on Second-Nearby Futures

This table reports the results of subsequent factor returns (%) predicted by crowding, where the returns are measured using the second nearby futures. The t-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Panel A: Momentum Returns Measured by Second-nearby Futures

	1 week		2-4 weeks	
Crowding	-0.065	-0.059	-0.148	-0.145
	(*-3.90*)	(*-3.13*)	(*-3.60*)	(*-3.26*)
Controls	No	Yes	No	Yes
R^2	1.3%	2.0%	2.1%	2.2%

Panel B: Basis and Value Factor Returns Measured by Second-nearby Futures

	Value				Basis			
	1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.066	-0.061	-0.158	-0.165	-0.039	-0.034	-0.103	-0.097
	(*-2.83*)	(*-2.53*)	(*-2.58*)	(*-2.63*)	(*-2.28*)	(*-1.91*)	(*-2.36*)	(*-2.06*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.9%	1.2%	1.7%	2.2%	0.4%	0.8%	0.9%	1.5%

Table A3: Robustness Tests Based on Alternative Factor Portfolio Construction Methods

This table reports the results of subsequent factor returns (%) predicted by crowding, where the factor portfolio are constructed by alternative methods. The t-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Panel A: Momentum Returns based on 6-month and 9-month Construction Windows

	6 months				9 months			
	1 week		2-4 week		1 week		2-4 week	
Crowding	-0.045	-0.040	-0.090	-0.091	-0.066	-0.067	-0.154	-0.149
	(*-2.76*)	(*-2.06*)	(*-2.00*)	(*-1.88*)	(*-3.90*)	(*-3.46*)	(*-3.87*)	(*-3.51*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.6%	0.9%	0.8%	0.8%	1.1%	1.4%	2.2%	3.2%

Panel B: Basis and Value Factor Constructed by Alternative Methods

	Value Factor Based on Past 5-Year Returns				Basis Factor Based on Second-Nearby Contracts			
	1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.045	-0.048	-0.105	-0.122	-0.043	-0.036	-0.132	-0.129
	(*-2.93*)	(*-3.00*)	(*-2.61*)	(*-2.87*)	(*-2.48*)	(*-1.97*)	(*-3.35*)	(*-3.08*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.5%	0.9%	0.8%	1.8%	0.5%	1.0%	1.6%	2.4%

Table A4: Robustness Test Based on Number of Traders

This table reports the results of subsequent factor returns (%) predicted by crowding, where the crowding measure is constructed using the number of non-commercial traders. The t-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Panel A: Momentum Factor Returns and Crowding Based on the Number of Traders

	1 week		2-4 weeks	
Crowding	-0.140	-0.092	-0.789	-0.766
	(*-1.69*)	(*-1.01*)	(*-3.78*)	(*-3.35*)
Controls	No	Yes	No	Yes
R^2	0.2%	0.9%	2.0%	2.2%

Panel B: Value and Basis Factor Returns and Crowding Based on Number of Traders

	Value				Basis			
	1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.297	-0.279	-0.780	-0.833	-0.085	-0.057	-0.386	-0.360
	(*-2.42*)	(*-2.16*)	(*-2.68*)	(*-2.78*)	(*-0.95*)	(*-0.60*)	(*-1.85*)	(*-1.60*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.6%	1.2%	1.4%	2.1%	0.1%	0.6%	0.4%	1.1%

Table A5: Crowding Constructed Based on Smoothed Hedging Pressure

In this table, instead of detrending the non-commercial's net-long position, we construct the crowding measure by deducting the smooth hedging pressure from the commercials net-long position. In Panel A, we conduct a Fama-MacBeth regression to predict next-period returns of individual commodities. Panel B lists the results of the predictability of the crowding on the subsequent factor returns.

Panel A: Fama-MacBeth Regression for Individual Commodities

Subsequent Returns	1 week		2-4 weeks	
Crowding	*-0.018*	*-0.018*	*-0.034*	*-0.018*
	(*-5.80*)	(*-3.94*)	(*-4.02*)	(*-1.79*)
Controls	No	Yes	No	Yes
R^2	4.70%	35.46%	4.63%	35.11%

Panel B: Predictability of Crowding on Three Factors

	Momentum				Value				Basis			
	1 week		2-4 weeks		1 week		2-4 weeks		1 week		2-4 weeks	
Crowding	-0.030	-0.034	-0.116	-0.136	-0.046	-0.068	-0.098	-0.156	-0.032	-0.026	-0.086	-0.078
	(*-2.73*)	(*-2.29*)	(*-3.97*)	(*-3.38*)	(*-2.72*)	(*-2.96*)	(*-2.09*)	(*-2.56*)	(*-2.57*)	(*-1.70*)	(*-2.53*)	(*-1.91*)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.44%	1.43%	2.11%	2.52%	0.69%	1.60%	1.10%	2.23%	0.48%	0.77%	1.10%	1.44%

Table A6: Crowding Based on the Money Manager's Positions from DCOT data: Individual Commodity Level

This table reports the regression in which individual commodity return are regressed on the crowding measure based on DCOT data. Both Fama-Macbeth and panel regressions (double fixed effects) are employed. The t-statistics in brackets are adjusted using the Newey-West method with thirteen lags.

Subsequent Returns	Fama Macbeth		Panel	
	1 week	**2-4 weeks**	**1 week**	**2-4 weeks**
Crowding	-0.028	-0.072	-0.012	-0.025
	(*-3.28*)	(*-3.54*)	(*-4.64*)	(*-3.50*)
Q	-0.058	-0.060	-0.039	-0.057
	(*-4.28*)	(*-2.30*)	(*-4.29*)	(*-2.99*)
SHP	0.003	0.014	-0.004	-0.005
	(*1.36*)	(*2.26*)	(*-1.12*)	(*-0.51*)
Basis	0.005	0.007	-0.001	-0.008
	(*1.89*)	(*1.01*)	(*-0.25*)	(*-1.51*)
Lagged Ret	0.047	0.008	0.021	-0.011
	(*3.25*)	(*0.34*)	(*1.86*)	(*-0.63*)
R^2	29.7%	29.4%	24.6%	25.1%