The Impact of Crowding in Alternative Risk Premia Investing*

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Abstract

Crowding is a major concern for investors in the alternative risk premia space. By focusing on the distinct mechanics of various systematic strategies, we contribute to the discussion with a framework that provides insights on the implications of crowding on subsequent strategy performance. Understanding such implications is key for strategy design, portfolio construction, and performance assessment. Our analysis shows that divergence premia, like momentum, are more likely to underperform following crowded periods. Conversely, convergence premia, like value, show signs of outperformance as they transition into phases of larger investor flows.

JEL Classification Codes: G11, G12, G14

Keywords: Crowding, Alternative Risk Premia, Divergence, Convergence

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Crowding risk is listed as one of the most important impediments for investing in alternative risk premia (ARP, henceforth) for the clients of asset managers and sell-side banks that are active in the ARP space, based on the recent MJ Hudgon Allenbridge survey. These responses echo the numerous media articles and information memos by various financial institutions over the recent years debating whether the rapidly growing ARP space is crowded or otherwise. Expectedly, Giamouridis (2017) in his recent editorial at the *Financial Analysts Journal* calls for further research on this topic and in particular on “what makes a sensible ex-ante measure of crowding” as well as on “how such measures are associated with the performance of factor portfolios and under what market conditions.”

We contribute to this industry debate by exploring the mechanics of the various ARP in the event of investor flows, and study the implications of crowdedness on subsequent performance. The results of this analysis can have significant consequences for ARP providers and investors alike in terms of strategy design, performance and risk assessment, portfolio construction, and ultimately dynamic factor allocation.

The term “crowding” is generally associated with a number of different notions. It can be related to estimates of the overall size of the ARP industry and therefore the consequences of a broad unwinding like the “quant meltdown” of August 2007 (Khandani and Lo, 2007; Khandani and Lo, 2011). It can be related to market impact and therefore strategy capacity (Frazzini, Israel, and Moskowitz, 2012; Novy-Marx and Velikov, 2015; Ratcliffe, Miranda, and Ang, 2017). The notion of crowding that we focus on relates to the response of systematic premia, at the strategy level, following periods identified as crowded.

We specifically draw inspiration from Stein’s (2009) presidential address at the American Finance Association, where he comments: “[…]* complications arise when, in the process of pursuing a given trading strategy, arbitrageurs inflict negative externalities on one another. […] The first [complication] might be termed a “crowded-trade” effect. [An arbitrageur] cannot know in real time exactly how many others are pursuing the same model and taking the same position.

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1 The MJ Hudson Allenbridge Systematic Factor Market Review was conducted from July to September 2017 and is available at [https://www.mjhusden.com/download/systematic-factor-market-review/](https://www.mjhusden.com/download/systematic-factor-market-review/).
as him. This [...] creates a coordination problem and [...] in some cases can result in prices being pushed further away from fundamentals.”

The cornerstone of our methodology is the classification of the ARP strategies into divergence and convergence premia. Divergence premia, like momentum, lack a fundamental anchor and inherently embed a self-reinforcing mechanism (e.g. in momentum, buying outperforming assets, and selling underperforming ones). This lack of a fundamental anchor creates the coordination problem that Stein (2009) describes, which can ultimately have a destabilising effect. Conversely, convergence premia, like value, embed a natural anchor (e.g. the valuation spread between undervalued and overvalued assets) that acts as an self-correction mechanism (as undervalued assets are no longer undervalued if overbought). Extending Stein's (2009) views, such dynamics suggest that investor flows are actually likely to have a stabilising effect for convergence premia.

In order to test these hypotheses we use the pairwise correlation of factor-adjusted returns of assets in the same peer group (outperforming assets, undervalued assets and so on so forth) as a metric for crowding. This metric is motivated by recent work by Cahan and Luo (2013), Lou and Polk (2014) and Huang, Lou, and Polk (2018).

We provide empirical evidence in line with these hypotheses. Divergence premia within equity, commodity and currency markets are more likely to underperform following crowded periods, whereas convergence premia show signs of outperformance as they transition into phases of higher investor flows.

Our paper draws inspiration from a list of relevant topics in the literature: momentum crashes and their relationship to crowded trades (Lou and Polk, 2014; Chabot, Ghysels, and Jagannathan, 2014; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), volatility targeting of equity factors (Moreira and Muir, 2017; Barroso and Maio, 2018), and factor timing based on factor valuation (Arnott, Beck, and Kalesnik, 2016a; Arnott, Beck, and Kalesnik, 2016b; Asness, 2016; Asness, Chandra, Ilmanen, and Israel, 2017). The papers closest to our analysis are by Stein (2009), Lou and Polk (2014) and Huang et al. (2018).
1 Framework and Hypotheses

Factor premia are classified in the literature into risk-based premia and price anomalies, based on their respective economic drivers. For our purpose we use a different classification inspired by strategy mechanics at times when the strategies experience –all else being equal– large inflows of capital. We introduce the concepts of divergence and convergence premia, which we briefly discuss in this section.

1.1 Divergence Premia

Divergence premia function like positive-feedback loops, as the investor activity inflates the trading signal. Using cross-sectional momentum as an example, an investor takes a long position on recent outperforming assets and a short position on recent underperforming assets. Figure 1 illustrates the mechanics of this strategy following large capital inflows.

[Figure 1 about here]

All else being equal, significant flows into a momentum strategy result in short-term outperformance and therefore the first-order impact of crowding is positive from a profitability standpoint. Such outperformance renders the recent winners stronger and symmetrically renders the recent losers worse off. Put differently, when momentum performs strongly driven mechanically by net inflows, its turnover is likely to fall, as the investor remains invested in (or symmetrically keeps shorting) the same assets. Figure 2 validates this point empirically, by illustrating the strong negative correlation between the cumulative one-year turnover of a quarterly rebalanced equity momentum strategy (winner decile minus loser decile) on a global equity universe, and the contemporaneous one-year return of the strategy. This is effectively the positive-feedback loop that is described by Stein (2009) and Lou and Polk (2014).

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2 The strategy used in this analysis is a combination of three quarterly rebalanced strategies, each rebalancing in a different month of a quarter so to reduce path dependency. The result holds even if we constrain the sample period after 2010, hence excluding the very strong correction that the momentum strategy suffered in the first half of 2009; for an in-depth discussion of "momentum crashes", see Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016).
It becomes economically impossible for this bubble-like behaviour to be sustained in the long term.\textsuperscript{3} Investors that allocate onto divergence strategies may find it difficult to know when to stop, due to the lack on an economic anchor.\textsuperscript{4}

Following the above, we hypothesise that investor crowding is more likely to have a destabilising effect for divergence premia, as it can drive prices away from fundamentals. This, in turn, increases the likelihood of an adverse factor correction. We test this hypothesis in the empirical part of the paper. The statistically significant negative relationship between funding liquidity and momentum strategies, whereby such strategies tend to underperform when funding liquidity becomes scarce is in line with this conjecture (Asness, Moskowitz, and Pedersen, 2013).

### 1.2 Convergence Premia

Contrary to divergence premia, convergence premia naturally embed a self-correction mechanism and function like negative-feedback loops. Using cross-sectional value as an example, buying undervalued (selling overvalued) assets results in relative price appreciation (depreciation) and therefore in valuation spread convergence.\textsuperscript{5} Figure 3 illustrates this dynamic.

All else being equal, significant flows into a value strategy would mechanically result in short-term outperformance, as the valuation spread shrinks and, at the margin, can

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\textsuperscript{3} If anything, as momentum outperforms, value investors become progressively more likely to step in to take advantage of the wider valuation spreads.

\textsuperscript{4} Investors might actually have an incentive to stay invested in divergence strategies, like cross-sectional momentum, even when the crash risk is known to be high as shown by Chabot et al. (2014).

\textsuperscript{5} Throughout the paper we consider equity value as the systematic cross-sectional strategy in the spirit of Basu (1977), Basu (1983), and Fama and French (1992), as opposed to the Graham and Dodd (1934) value investing whereby an investor seeks for stocks whose market price is below their intrinsic value. The former is a relative (cross-sectional) value trade and lends itself more naturally to a systematic market neutral strategy, whereas the latter is an absolute/univariate value trade and is more related, though not exclusively so, to more discretionary and stock-picking strategies.
theoretically completely vanish. However, contrary to divergence premia, investors allocating onto convergence premia have a natural anchor that signals the end of a profitable opportunity. At that stage a value investor would turn the portfolio over completely in order to allocate to any new value opportunities. Larger investor flows in convergence premia can bring faster convergence of valuation spreads (i.e. opportunities would go away faster; the time of convergence of the valuation spread, $\tau$, as shown in Figure 3, should be inversely related to flows) and hint towards the necessity of a more responsive portfolio turnover mechanism.

Figure 4 validated this point by illustrating the positive relationship between turnover and performance for a quarterly rebalanced value strategy, using the book-to-price ratio as the value metric. The relationship is not as strong as in the case of momentum in Figure 2, because a value portfolio rebalances if either prices or book values change cross-sectionally; see Ilmanen, Nielsen, and Chandra (2015) for relevant discussion.

Following the above, we hypothesise that anchored strategies are more resilient to incoming flows. Such inflows should have a stabilising effect, as prices converge faster towards fundamentals (all else being equal). Focusing on the long term, it could be argued that excessive investor crowding, all else being equal, can progressively squeeze valuation spreads, to the point that all valuation levels in the cross-section collapse onto the same level. This is equivalent to arguing that the value premium can vanish as a result of overcrowding.

Whether the value premium (or any premium) can completely vanish due to excessive crowding is probably more of a point on equilibrium asset pricing and is beyond the scope of our analysis. Having said that, one can argue that more systematic flows might be necessary but not sufficient to wipe systematic premia. When value outperforms it eventually transitions into a momentum cycle, because the undervalued assets that outperform become more likely to screen as winning assets for momentum investors, who subsequently may take the lead and

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6 As for momentum in Figure 2, the strategy used here is a combination of three quarterly rebalanced strategies, each rebalancing on a different month of a quarter so to reduce any path dependency.
potentially drive prices away from fundamentals, and so on so forth. This dynamic transition between convergence and divergence strategies is the reason why Stein (2009) argues that “while a larger number of sophisticated arbitrageurs certainly makes life more competitive and less profitable for the arbitrageurs themselves, it need not make the world a better place for those who look to asset prices to provide a reliable reflection of underlying fundamental values”.7

2 Methodology

We next provide an overview of the cross-asset dataset and of the specifications for strategy construction, and subsequently present in detail the steps towards estimating the measure of crowdedness used in our empirical analysis.

2.1 Data and Strategy Construction

The academic literature on the topic of crowding has so far been primarily concentrated to an equities universe (Cahan and Luo, 2013; Lou and Polk, 2014; Huang et al., 2018). In an attempt to establish pervasiveness and robustness for our findings, we expand our focus across various asset classes and risk premia strategies. Table 1 contains all the details about the asset universes and all the respective strategy specifications. We briefly discuss below the main details.

For the purposes of our analysis we use (a) a global tradeable and liquid developed markets equities universe (September 2004 to May 2018), (b) the 24 constituents of the S&P GSCI Commodity Index (January 1999 to May 2018), and (c) 26 developed and emerging

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7 One can also draw parallels between the momentum-value paradigm and the theory of boom/bust cycles of George Soros (2010). This theory contains two “reflexive feedback loops that characterize financial markets”, one negative and one positive. As he explains “negative feedback is self-correcting, and positive feedback is self-reinforcing. Thus, negative feedback sets up a tendency toward equilibrium, but positive feedback produces dynamic disequilibrium. [...] A positive feedback process that runs its full course is initially self-reinforcing in one direction, but eventually it is liable to reach a climax or reversal point, after which it becomes self-reinforcing in the opposite direction. But positive feedback processes do not necessarily run their full course; they may be aborted at any time by negative feedback.”
market currency pairs against the USD (January 2000 to May 2018). The data is collected from Worldscope and Axioma for the equities universe, and from Bloomberg for the commodities and currency universes.

We conduct our analysis on a broad range of stylized cross-sectional risk premia strategies. We specifically focus on (a) value (book-to-price), size (market capitalisation), momentum (residual of cross-sectional regression of past 12-month return, excluding most recent month, against stock volatility), quality (return-on-assets) and low beta (beta to the MSCI World Index) strategies within equities, (b) momentum (12-month return) strategies within commodities, and (c) value (purchasing power parity) and momentum (12-month return) strategies within currencies.

Each strategy is constructed on a cash-neutral basis by taking a long position in an equally-weighted portfolio of top-ranked assets and a short position in an equally-weighted portfolio of bottom-ranked assets. For the equity strategies we use top and bottom deciles, whereas for the smaller commodity and currency universes we use top and bottom thirds, which effectively amounts to taking a long position on the top eight assets and a short position on the bottom eight assets.

2.2 Measuring Crowdedness

The role of financial markets is to balance the supply and demand for assets. Naturally, as the market clears there is a seller for every buyer. Measuring crowdedness is therefore equivalent to identifying groups of investors, who share common investment objectives and allocate to (or deallocate from) assets with a common characteristic (e.g. high momentum assets). The larger these groups of investors are and equivalently the larger the synchronous inflows onto the top-ranked assets and outflows from the bottom-ranked assets, the larger the implied level of crowding in the respective premium.

Following the above, there are different ways one can proxy for investor crowdedness. One can estimate the level of crowdedness using either the inputs to the financial markets system, such as flows data or positioning data (e.g. regulatory filings), or using the outputs of the system, such as asset co-movement or potentially valuation spreads. Flows and positioning
data have a number of limitations in terms of depth, timeliness of availability, and historical
and asset class coverage. For these reasons, we proceed with price-based crowdedness
metrics.

The principal idea for the crowdedness metric that we use is that synchronous flows into a
portfolio of assets (from a large group of investors with similar investment objectives) should,
all else being equal, increase the co-movement of these assets, above and beyond what is
implied by the overall market (beta) and potentially other factors that drive cross-sectionally
asset returns.

Cahan and Luo (2013) are the first to use pairwise correlations of a group of US stocks that
share a common characteristic (e.g. top momentum stocks) as a proxy of crowdedness.
Additionally, they also use securities lending data to form the difference in utilization between
high-scoring and low-scoring baskets of stocks; the larger the utilization of the unattractive
basket of stocks, the more crowded the factor is considered. They find that both metrics
(correlation-based, utilization-based) exhibit rather similar results in terms of identifying
factor crowded periods.

Lou and Polk (2014) and Huang et al. (2018) use pairwise correlations to proxy for
crowdedness within US equity momentum and low beta portfolios respectively, and find that
such crowdedness metrics are statistically strongly forecasted by past institutional ownership
of the long baskets of these portfolios, by past assets under management of long-short equity
hedge funds and finally by past strategy performance (which they claim can be indicative of
performance chasing). This empirical evidence provides support in the use of pairwise excess
correlations as a well-accepted measure of crowdedness.

The estimation framework that we use for each strategy is outlined below:
• For each week $t$, we identify the top-scoring and bottom-scoring assets of the factor of
  interest, e.g. the top and bottom momentum stocks.
• For each asset $i$ of the top and bottom baskets, we estimate the factor-adjusted residual
  returns $\epsilon_{it}$ by regressing the past $\Delta = 52$ weekly returns ($5 \times 52$ weekly returns for
value strategies\textsuperscript{8}) on an asset class-specific factor model, that excludes the factor of interest:

\[ r_{i,t} = \alpha_i + \sum_j \beta_{i,j} \cdot F_{j,t} + \epsilon_{i,t}, \quad t \in \Delta \]  

(1)

Table 1 contains details for the asset-class specific factor model used for each universe. For example, the factor model used for the equities strategies is a four-factor model, containing the market (as proxied by the MSCI World Index), size, value and momentum factors.\textsuperscript{9}

- The last step amounts to estimating the signed average pairwise correlation between all residual returns of the assets in the top and bottom baskets:

\[ CoMetric_t = \frac{\sum_{i<j}s_{i,t}s_{j,t}\rho(\epsilon_{i,t}\epsilon_{j,t})}{N(2N-1)} \]  

(2)

where \( s_{i,t} = +1 \) if asset \( i \) belongs to the top basket or \( s_{i,t} = -1 \) if it belongs to the bottom basket. This is intended to allow the construction of a joint measure of asset excess co-movement that combines the information from both top and bottom factor

\textsuperscript{8}Asness et al. (2013) argue that value strategies are related to long-term reversal strategies and use the negative of the past 5-year asset performance as a value signal across various asset classes. This is supported by evidence in Fama and French (1996), who find that equity portfolios based on either this metric or based on book-to-price ratio are largely correlated to each other. More recently, Gerakos and Linnainmaa (2018) find that within an equities universe, the cross-sectional time variation in book-to-price ratios is primarily driven by the cross-sectional time variation of stock prices as opposed to the cross-sectional time variation of book values. Put differently, a cheap stock is more likely to have become a cheap stock due to a significant long-term price fall (relative to the cross-section of stocks), rather than due to a significant increase in book value. This justifies the use of long-term price-based metrics as valuation metrics.

\textsuperscript{9}It is important to clarify that we always use the residuals of a factor model that does not account for the factor of interest. As an example, when estimating the \textit{CoMetric} for momentum, we use the residuals from fitting the equities factor model from Table 1 to each asset \( i \) in the top and bottom baskets, without controlling for momentum:

\[ r_{i,t} = \alpha_i + \beta_i \cdot Mkt_t + s_i \cdot Size_t + v_i \cdot Value_t + \epsilon_{i,t} \]

Symmetrically, when estimating the \textit{CoMetric} for value, we use the residuals of a regression that does not control for value:

\[ r_{i,t} = \alpha_i + \beta_i \cdot Mkt_t + s_i \cdot Size_t + m_i \cdot Momentum_t + \epsilon_{i,t} \]

In this way, the factor correlation between value and momentum factors is already accounted for and does not contaminate the respective \textit{CoMetric} estimates.
baskets. After all, a long-short premium can become crowded if there is excess buying demand for the long basket, or excess selling pressure for the short basket, or both.\textsuperscript{10}

We end up with a weekly time-series of co-movement for each factor premium in each of the asset classes. This \textit{CoMetric} is used in order to identify most and least crowded periods and therefore explore the impact of crowding on subsequent strategy performance. Following Lou and Polk (2014), weeks identified at the top 20% of the \textit{CoMetric} are classified as most crowded, whereas weeks identified at the bottom 20% are classified as least crowded.\textsuperscript{11}

Figure 5 presents an example of the \textit{CoMetric} estimation for the equity momentum and equity value premia. Top and bottom deciles of both premia are determined on a weekly basis and the average levels of asset excess co-movement are estimated as just described.\textsuperscript{12}

There are a few important observations we should discuss. In theory, regression residuals, like those used in the estimation of the \textit{CoMetric} should be cross-sectionally uncorrelated and the time-series of the \textit{CoMetric} should be statistically indistinguishable from zero. However, the evidence suggests otherwise. Stocks in the top and bottom momentum and value baskets

\textsuperscript{10}Cahan and Luo (2013), Lou and Polk (2014), and Huang et al. (2018) estimate similar metrics of co-movement using only the top or the bottom factor basket. We consider the joint metric as a more appropriate metric of co-movement, as it does not only capture the co-movement within these two baskets, but also accounts for the cross effects. In robustness tests, we have repeated our analysis based on metrics estimated using either the top or the bottom basket; our results remain broadly unaltered (and at times even improve) both qualitatively and quantitatively.

\textsuperscript{11}We require at least 1.5 years of subsequent performance for a week to be classified as most or least crowded; hence, the selection ends 1.5 years before the end of our sample period.

\textsuperscript{12}In unreported results we have estimated the co-movement metric separately for the top or the bottom basket. We find that the level of excess co-movement of the top-ranked assets exhibits a large correlation with the level of the excess co-movement of the bottom-ranked assets. This correlation in crowdedness metrics across top-ranked and bottom-ranked stocks is 0.51 for equity momentum; Lou and Polk (2014) use the same methodology for a US equities universe and report a correlation of 0.524 for momentum between 1964 and 2010. Similarly, we estimate the correlation between the two crowdedness metrics for equity value to be equal to 0.43. This evidence is rather supportive of the use of the \textit{CoMetric} as a proxy of crowdedness, because periods of abnormal flows in or out of certain systematic strategies should be broadly reflected across the entire cross-section of assets. More importantly, the use of the joint metric allows us to merge the information content of the two baskets and also account for any cross effects, which are not captured by the separate metrics.
exhibit time-varying, yet statistically strong cross-dependence, which can be interpreted as excess demand for these baskets, hence reflecting crowding dynamics.\textsuperscript{13}

The time-series of the CoMetric is clearly not constant over time, but most importantly, it does not necessarily increase over time. Contrary to a passive allocation in a market capitalization-weighted index, ARP strategies allocate dynamically across different assets and the portfolios are turned over on a regular basis. This means that whatever asset ranks today as a top one, based on some factor characteristic, is not necessarily a top-ranked asset the day before or the day after. This difference between passive index investing and systematic ARP investing renders the notion and impact of crowding fundamentally different between the two.

Another characteristic of the CoMetric is that it can be quite persistent. There are periods of higher levels of asset excess co-movement and periods of lower levels of asset excess co-movement. We then empirically test whether the level of asset excess co-movement has significant implications for the subsequent return profile of the various ARP strategies.

3 Empirical Analysis

3.1 Divergence Premia

Starting from divergence premia and in particular equity cross-sectional momentum, Figure 6 contrasts the average performance of a buy-and-hold cross-sectional momentum strategy (winners decile minus losers decile) over a period of two years following the most crowded periods against the performance following the least crowded periods.\textsuperscript{14} Alongside the average performance we present 95\% confidence interval bands estimated using Newey and West (1987) robust standard errors. Additionally, the top panel of Table 2 reports the average

\textsuperscript{13}The CoMetric for momentum and value, presented in Figure 5, is strictly positive for the entire sample period, exhibiting an average value of 1.42\% (with a standard deviation of 0.59\%) for momentum, and 3.23\% (with a standard deviation of 0.66\%) for value (based on the five-year estimation). Similarly strictly positive estimates are documented for the rest of equity premia studied; these estimates are available upon request.

\textsuperscript{14}ARP strategies dynamically rebalance as time progresses and cross-sectional ranks shift. Asness (2016) accordingly suggests against running long-horizon regressions between current valuation and future performance, especially for portfolios with very large turnover. To overcome this structural feature and directly relate current levels of crowdedness to future performance, we track buy-and-hold portfolios based on current ranks, over the entire two-year horizon.
holding period returns of the strategy over the first month, the first six months, the first year and the second year following high levels of asset excess co-movement, low levels of asset excess co-movement, as well as the differential return between these two regimes ("H-L"). The t-statistics are estimated using Newey and West (1987) robust standard errors.

[Figure 6 about here]

[Table 2 about here]

Conditioning the performance of the equity momentum strategy on the prior level of crowdedness results in statistically different results. Even if a momentum strategy initially benefits from its self-reinforcing mechanism independent to the earlier crowdedness state (as per Table 2 the strategy delivers positive returns over the first month following both crowded and noncrowded periods, with the difference being statistically insignificant), when such herding reaches extreme levels, the strategy is more likely to suffer a drawdown. In line with our hypothesis, the strategy underperforms following high levels of crowding, while strongly outperforming following low levels of crowding over the first six months to a year with the t-statistics of the H-L spread being $-5.30$ and $-9.12$ respectively. Our findings echo those by Lou and Polk (2014) and Chabot et al. (2014).

Figure 7 extends this analysis to a broad universe of divergence premia across asset classes, using for each premium the respective CoMetric indicator for the identification of high and low asset excess co-movement regimes. In particular, we look at momentum strategies outside of equities, and in particular in currency and commodity markets, and we also look at equity low beta and equity quality strategies.\(^{15}\) Table 2 reports again the relevant statistics.

\(^{15}\) Huang et al. (2018) explain why equity low beta can be thought of as a divergence premium. When low beta stocks outperform (and high beta assets underperform), their respective price movement results in a reduction (increase) in firm leverage when expressed for example as the debt-to-equity ratio. This, in turn, results in the stocks’ betas falling (increasing) even further, as it follows from Proposition II of Modigliani and Miller (1958) hence rendering the respective low (high) beta stocks highly likely to maintain their top (bottom) rank in the cross-sectional distribution of betas. As far as quality is concerned, we classify it also as a divergence premium following the works by Asness, Frazzini, and Pedersen (2018) and Bali, Del Viva, Lambertides, and Trigeorgis (2018), who establish the links between quality/profitability and low beta.
Our findings for equity momentum are pervasive across all divergence premia that we study. None of the premia exhibit statistically different patterns over the first month following a high or low crowded regime (all H-L t-statistics are small), as they are all likely to be experiencing the later phases of their self-reinforcing activity. However, over a six-month to one-year horizon, all divergence premia, unequivocally, underperform following high levels of asset excess comovement, and outperform following low levels of asset excess co-movement. The t-statistics in the H-L spread reach maximum levels around the annual holding horizon for most of the premia. Indicatively, for the annual horizon these t-statistics are $-8.41$ for equity low-beta, $-5.14$ for equity quality, $-3.07$ for currency momentum and $-2.92$ for commodity momentum; statistical significance at 1% level is established across all premia.

Overall, our results provide empirical support to the conjecture of Stein (2009) that non-anchored divergence strategies can cause a coordination problem to investors, who cannot know in real time how many other investors are invested. As a result, when such strategies become crowded they are more likely to underperform. Conversely, lower levels of asset excess co-movement are more accommodative for outperformance. These results can have important implications if one is tempted to build a factor timing model using CoMetric indicators.

### 3.2 Convergence Premia

We next provide the same analysis for convergence premia. Figure 8 presents the performance of a buy-and-hold cross-sectional value strategy over a period of two years following the most crowded periods against the performance following the least crowded periods and the top row of Table 3 reports relevant performance statistics.
The behaviour of the strategy is completely opposite to what was documented for divergence premia. Higher levels of asset excess co-movement that are reflective of investor synchronous flows, constitute a catalyst for future outperformance. Conversely, low levels of asset comovement are associated with poor future performance. The t-statistic of the H-L spread is again maximised for the annual horizon and is equal to +11.78.

We then extend the analysis to other convergence premia, namely FX value and equity size. Figure 9 presents the conditional buy-and-hold performance and the relevant performance statistics are reported in the bottom rows of Table 3. In line with our hypothesis and with the evidence for equity value, FX value also benefits from increased asset co-movement, delivering statistically positive holding returns that reach a maximum level around the annual horizon, with a t-statistic of the H-L spread being +5.86.

The only premium that appears to be an outlier in the group of ARP strategies we study is equity size (small minus large caps). The prior level of asset excess co-movement does not bear any relevant information for a size portfolio for the first six months, with the portfolio delivering statistically strong returns of 2.19% following high levels of asset excess co-movement and 4.76% following low levels of asset excess co-movement, with the difference being statistically insignificant (t-statistic of −1.58). These positive returns continue up to a year (3.55% and 7.67% respectively, with the difference now becoming marginally statistically significant with a t-statistic of −2.12).

We attribute the lack of a positive and statistically significant H-L spread for the equity size portfolio to some potential effects. It is likely that there is an omitted factor in our estimation of the size CoMetric that masks the commonality in the excess movement in the small-cap and large-cap baskets. Besides, recent work by Alquist, Israel, and Moskowitz (2018) challenges the very existence of the size factor as a profitable premium. They provide empirical evidence
whereby the size premium is not statistically significant across countries, across sample periods and different implementations.

Notwithstanding the potential misalignment of the size premium to our overall hypothesis, the value strategies within equity and currency markets offer support to our hypothesis that the impact of crowdedness has different implications for the profitability of the different ARP strategies as their respective strategy mechanics would suggest.

### 3.3 Relevance to Investors

Our objective has been to explore the impact of strategy-level crowding to subsequent performance and show that strategy mechanics are critical in such a relationship. Our findings suggest that crowding is not always a catalyst for underperformance and should not be treated as such by investors. Our results have direct implications for risk management and multi-factor portfolio construction.

Investors should consider how to risk-manage strategies with divergence dynamics, especially when these strategies experience net flows. Volatility-targeting is one well-studied systematic way that has been shown to improve risk-adjusted returns of divergent strategies, like momentum and betting-against-beta (Barroso and Santa-Clara, 2015; Moreira and Muir, 2017; Barroso and Maio, 2018). In unreported results we find that divergence premia exhibit higher volatility following crowded periods (in agreement with Lou and Polk, 2014), which justifies the use of a volatility-targeting mechanism.

Conversely, applying volatility-targeting to convergent strategies might not necessarily improve risk-adjusted returns. In unreported results, we find that convergent premia exhibit lower volatility following crowded periods. In their analysis on the impact of volatility-targeting on equity factors, (Moreira and Muir, 2017) find that the Fama and French (1993) HML factor does not statistically strongly benefit from volatility-targeting.

Put together, the above have implications for practitioners that build multi-factor portfolios. Popular risk-based schemes like risk parity (also known as Equal Risk
Contribution) appear more suitable for portfolios of divergent strategies, but not necessarily for portfolios of convergent strategies. Future research should look at such dynamics.

4 Conclusions and Future Work

The main objective of this paper has been to study one market perception that investor crowding in ARP strategies can have a negative impact on performance. Using two stylized models for the mechanics of ARP strategies, namely divergence and convergence, we have shown that different ARP strategies may respond differently to investor flows. Such flows can have significant implications in the risk-return profile of systematic strategies, of which ARP providers and investors should be aware so to improve strategy design, risk and return assessment and ultimately portfolio construction.

These findings do not obviously mean that an event of sudden unwinding of cross-asset risk premia portfolios does not represent a considerable risk for an ARP investor. Such an event does clearly represent a risky possibility. However, our focus has not been the assessment of performance in the event of a sudden unwinding; the actual impact is merely mechanical. Our focus has been rather to assess the impact of inflows (as opposed to orchestrated outflows) into ARP strategies on subsequent strategy performance. Our objective is to provide ARP investors with clarity on the premia dynamics as they navigate through market cycles and ultimately provide them with the tools to better design and rebalance their portfolios.

A number of follow-up questions naturally emerge from our analysis and could serve as topics for future research. The predictive ability of crowding indicators for future ARP performance renders them as candidate signals for factor rotation/timing, which is a topic that has been heavily debated recently (Arnott et al., 2016a; Asness et al., 2017). To our knowledge, the only attempt to incorporate such crowding indicators in a systematic allocation framework is by Dichtl, Drobetz, Lohre, Rother, and Vosskamp (2018).

Another topic is the viability of factor premia in the presence of significant investor flows and whether more crowding in the ARP space degrades long-term expected returns. From an
empirical standpoint, ARP viability becomes also almost synonymous to investigating whether there is substantial "other side" to sustain increased flows. The most relevant work in this space is by Ilmanen (2016) and Blitz (2017).
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* Winners are not formulaically more expensive than losers, even though this has generally been the case historically.

**Figure 1: Divergence Premia**

**Notes:** The figure presents the dynamics of a divergence premium in the presence of inflows (all else being equal). A cross-sectional momentum strategy (winners versus losers) is used as an illustrative example.

**Figure 2: Momentum performance versus turnover**

**Notes:** The figure presents the contemporaneous relationship between the annual turnover of an equities momentum strategy (top versus bottom decile) and its rolling one-year performance. The strategy is a combination of three quarterly rebalanced strategies that rebalance on different months of a quarter. Sample period: December 2005 to April 2018. Universe: global DM equity universe.
**Figure 3: Convergence Premia**

**Notes:** The figure presents the dynamics of a convergence premium in the presence of inflows (all else being equal). A cross-sectional value strategy (undervalued versus overvalued assets) is used as an illustrative example.

**Figure 4: Value performance versus turnover**

**Notes:** The figure presents the contemporaneous relationship between the annual turnover of an equities momentum strategy (cheap versus expensive decile) and its rolling one-year performance. The strategy is a combination of three quarterly rebalanced strategies that rebalance on different months of a quarter. Sample period: December 2005 to April 2018. Universe: global DM equity universe.
Figure 5: *CoMetric for Equity Momentum and Value*

Notes: The figure presents the average pairwise excess correlation for the winners and losers (Panel A) or for the cheap and expensive stocks (Panel B) of a global equities universe. The estimation is weekly, and the past 52 weekly returns (or 5*52 weekly returns for value) of each stock are used for the estimation. The returns of the assets in the momentum (value) baskets are factor-adjusted for the market, size and value (momentum) factors. Sample period: September 2004 (first estimates become available 52 or 5*52 weeks later accordingly) to May 2018.
Figure 6: *Equity Momentum Event Study*

**Notes:** The figure presents the average buy-and-hold performance of a long-short equity momentum portfolio (top minus bottom equally-weighted deciles) over a two-year period following the most crowded periods or the least crowded period. The crowdedness is measured on a weekly basis using the *CoMetric*. The figure contains 95% confidence interval bands estimated using Newey and West (1987) standard errors. The sample period used for the determination of most and least crowded periods is from October 2005 to May 2018.

Figure 7: *Divergence Event Study*

**Notes:** The figure presents the average buy-and-hold performance of various long-short divergence portfolios (see Table 1 for specification details) over a two-year period following the most crowded periods or the least crowded period. The crowdedness is measured on a weekly basis using the *CoMetric* of each strategy.
**Figure 8: Equity Value Event Study**

Notes: The figure presents the average buy-and-hold performance of a long-short equity value portfolio (top minus bottom equally-weighted deciles) over a two-year period following the most crowded periods or the least crowded period. The crowdedness is measured on a weekly basis using the CoMetric. The figure contains 95% confidence interval bands estimated using Newey and West (1987) standard errors. The sample period used for the determination of most and least crowded periods is from October 2009 to May 2018.

**Figure 9: Convergence Event Study**

Notes: The figure presents the average buy-and-hold performance of various long-short convergence portfolios (see Table 1 for specification details) over a two-year period following the most crowded periods or the least crowded period. The crowdedness is measured on a weekly basis using the CoMetric of each strategy.
| **Table 1: Overview of Data** |
|-------------------------------|
| **Equities**                  |
| **Universe**                  | Global Developed Markets Universe          |
| **Period**                    | Sept. 2004 – May 2018                      |
| **Factor Model**              | 4-factor model: MSCI World Index, Size, Value, Momentum |
| **Test Portfolios**           | Top Decile / Bottom Decile, equally weighted |
| **Convergence**               | Value: Book-to-Price                       |
|                               | Size: Market Capitalisation                |
| **Divergence**                | Momentum: Residual of cross-sectional regression of past 12m return (excl. most recent month) against stock volatility (estimated over the same period) |
|                               | Quality: Return-On-Assets                  |
|                               | Low Risk: Beta to MSCI World Index         |
| **Source**                    | Worldscope, Axioma                         |

| **Commodities**               |
| **Universe**                  | 24 S&P GSCI Commodities:                  |
|                               | Chicago Wheat, Kansas Wheat, Corn, Soybeans, Coffee, Sugar, Cocoa, Cotton | Live Cattle, Feeder Cattle, Lean Hogs | WTI Crude Oil, Brent Crude Oil, Gas Oil, Heating Oil, RBOB Gasoline, Natural Gas | Aluminium, LME Copper, Lead, Nickel, Zinc | Gold, Silver |
| **Period**                    | Jan. 1999 – May 2018                      |
| **Factor Model**              | 2-factor model: GSCI Commodity Index, Carry |
| **Test Portfolios**           | Top Third / Bottom Third, equally weighted |
| **Divergence**                | Momentum: Past 12m return                  |
| **Source**                    | Bloomberg                                  |

| **FX**                        |
| **Universe**                  | 26 Developed and Emerging Market Currencies: |
|                               | AUD, BRL, CAD, CHF, CLP, CNH, CZK, EUR, GBP, HUF, ILS, INR, JPY, KRW, MXN, MYR, NOK, NZD, PHP, PLN, RUB, SEK, SGD, TRY, TWD, ZAR |
| **Period**                    | Jan. 2000 – May 2018                      |
| **Factor Model**              | 3-factor model: US Dollar Index, Carry, Momentum |
| **Test Portfolios**           | Top Third / Bottom Third, equally weighted |
| **Convergence**               | Value: Purchasing Power Parity            |
| **Divergence**                | Momentum: Past 12m return                  |
| **Source**                    | Bloomberg                                  |

**Notes:** The table presents details about the universe of assets used in the analysis.
Table 2: Performance of divergence premia conditional on the level of asset excess co-movement

|                | Obs. | Month 1 | Months 1-6 | Year 1     | Year 2     |
|----------------|------|---------|------------|------------|------------|
| EQ Momentum    |      |         |            |            |            |
| High           | 173  | 0.64%   | -2.25%     | -5.91%**   | 1.42%*     |
| Low            | 173  | 1.21%** | 4.58%**    | 6.86%**    | -0.52%     |
| H-L            |      | -0.57%  | -6.83%**   | -12.78%**  | 1.63%      |
| EQ Low Beta    |      |         |            |            |            |
| High           | 173  | -2.25%  | -13.75%**  | -20.11%**  | -6.97%     |
| Low            | 173  | 0.40%   | 3.61%**    | 8.74%**    | 9.26%**    |
| H-L            |      | -2.66%  | -17.36%**  | -28.85%**  | -16.25%*   |
| EQ Quality     |      |         |            |            |            |
| High           | 173  | -0.11%  | 3.64%**    | -4.74%**   | -0.60%     |
| Low            | 173  | 0.61%   | 4.16%**    | 8.72%**    | 0.53%      |
| H-L            |      | -0.72%  | -7.80%**   | -13.47%**  | -0.76%     |
| FX Momentum    |      |         |            |            |            |
| High           | 248  | 0.17%   | -0.21%     | -1.05%     | -0.04%     |
| Low            | 248  | 0.20%   | 1.04%**    | 1.38%**    | 1.46%**    |
| H-L            |      | -0.04%  | 1.26%**    | -2.44%**   | -1.43%*    |
| CO Momentum    |      |         |            |            |            |
| High           | 260  | 0.33%   | 1.28%      | -3.21%*    | 5.59%**    |
| Low            | 260  | 0.64%*  | 0.77%      | 2.32%      | 5.43%**    |
| H-L            |      | -0.31%  | 0.51%      | -5.53%**   | -0.18%     |

Notes: The table reports the average returns of buy-and-hold long-short divergence strategies across equity, currency and commodity markets following periods of high and low levels of asset excess co-movement. These periods are determined on a weekly basis using the level of CoMetric of each premium. The “H-L” rows report the differential return of the strategies following high vs. low level of asset excess co-movement. Statistical significance is reported using a single asterisk (*) for results that are significant on a 5% two-tail test basis and double asterisks (**) for results that are significant on a 1% basis. Newey and West (1987) robust standard errors are used in order to account for heteroskedasticity and serial correlation.
|          | Obs. | Month 1 | Months 1-6 | Year 1 | Year 2  |
|----------|------|---------|------------|--------|---------|
| EQ Value | High | 111     | 0.69%*     | 5.85%**| 5.45%** | -4.64%**|
|          | Low  | 111     | -0.85%*    | -5.71%**| -11.61%**| -6.91%*  |
|          | H-L  |         | 1.54%**    | 11.56%**| 17.05%**| 0.54%    |
|          | High | 173     | 0.86%**    | 2.19%**| 3.55%** | -4.63%**|
|          | Low  | 173     | 0.87%      | 4.76%**| 7.67%** | 2.19%    |
|          | H-L  |         | -0.00%     | -2.58% | -4.12%* | -7.41%**|
|          | High | 186     | 0.62%**    | 2.72%**| 5.04%** | 2.26%    |
|          | Low  | 186     | 0.29%**    | 0.94%**| 1.32%** | 0.97%**  |
|          | H-L  |         | 0.33%      | 1.78%**| 3.72%** | 1.29%    |

**Notes:** The table reports the average returns of buy-and-hold long-short convergence strategies across equity and currency markets following periods of high and low levels of asset excess co-movement. These periods are determined on a weekly basis using the level of CoMetric of each premium. The “H-L” rows report the differential return of the strategies following high vs. low level of asset excess co-movement. Statistical significance is reported using a single asterisk (*) for results that are significant on a 5% two-tail test basis and double asterisks (**) for results that are significant on a 1% basis. Newey and West (1987) robust standard errors are used in order to account for heteroskedasticity and serial correlation.