Research Insight

Manager Crowding and Portfolio Construction

Do Risk Models Cause Manager Crowding?

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Given that we all use similar software and data, read the same academic journals and are on the same broker-research email lists, is it any wonder that trades become crowded and outperformance is competed away?

Simon Neil Whiteley (Scottish Widows Investment Partnership)[1]

Introduction

Following the "quant meltdown" of August 2007, market observers and participants became concerned that quant strategies were leading to crowded trades. For example, Khandani and Lo (2007) note that too many quant managers were invested in the same strategies with too much leverage. Popular opinion often attributes crowding among mangers to a combination of effects. It is thought to be due largely to portfolio managers' use of similar alphas, and to be exacerbated by leverage and risk control mechanisms, such as risk policies and constraints. Quantitative managers, who typically follow a more structured and systematic portfolio construction process, are often thought to be at greater risk of crowding.

Another concern is that managers' widespread use of the same risk model in portfolio construction may promote crowding. While quantitative managers typically craft their own alphas, they often use risk models from firms that specialize in building these models; in this paper, we will refer to these as *standard* risk models. This has led investors to wonder whether using a standard risk model in portfolio optimization makes a quantitative manager more prone to crowded trades than using a *proprietary* risk model or a different portfolio construction technique. Surprisingly, there has been little analytical research done on these important issues.

In this paper, we take a first step in rigorously analyzing the impact that a risk model used in portfolio construction has on manager crowding. We address some of the common concerns about crowding by examining two questions:

- Does using a standard risk model in portfolio optimization promote crowding among managers?
- Does using a proprietary risk model avoid crowding?

To answer these questions, we first define what we mean by crowding, identify drivers of crowding, and illustrate their impact. A risk model's effect on manager crowding depends, in part, on how alphas used by different managers are related to each other and to the risk model factors. We explain how this works with some simple, intuitive examples. With the aid of a well established analytical framework, we show that:

- Using a standard risk model in portfolio construction does not invariably lead to crowding; in fact, it can differentiate managers.
- Using a proprietary risk model that incorporates a manager's alphas has limited power to reduce crowding—proprietary models may also increase the similarity of different managers' portfolios.

[1] Is it time for the quant investor to bounce back? FT Adviser, published February 27, 2012

While this study focuses on how a risk model affects manager crowding, we want to emphasize that the primary role of a risk model is to accurately forecast risk, to help build effective portfolios, and to aid in risk control and budgeting. Crowding is just one consideration.

What is the Question, Exactly?

There is no universally accepted definition of manager crowding. Two signs of crowding are frequently discussed: the propensity of many managers to hold similar positions and the high correlation in manager returns. Both worry investors seeking diversification among different managers. Overlap in manager holdings is most closely linked to the potential risks of the unwinding of crowded trades, while correlations among manager returns are due to similarities in holdings as well as the risk structure of the managers' bets.

In times of rising uncertainty, portfolio positioning and awareness of crowding takes on increased importance. This is because many investors may try to exit similar positions at the same time. As noted by several researchers,[2] the phenomenon of large numbers of traders exiting similar positions at the same time creates liquidity problems, because everyone is rushing to exit a "burning house." In order to leave, however, reaching the exit is not enough; you must persuade someone from the outside to take your place—and at not too large a cost.

What does it mean to be more crowded?

We aim to investigate the role that a risk model plays in portfolio optimization in promoting or mitigating crowding. For example, does using the same risk model make managers' holdings more similar? That raises the question: more similar than what? To answer this, we need a benchmark for comparison. In our view, a natural way to examine whether risk models promote crowding is to compare the correlations of managers' holdings (or returns) obtained by different portfolio construction methods. In the simplest case, we can compare the correlations of managers' alphas and the correlations of their holdings. If portfolio managers' holdings are more correlated than their alphas, we conclude that the method used to generate these holdings promotes crowding relative to the "*naïve" approach of building a portfolio that makes an asset's weight proportional to its alpha*.

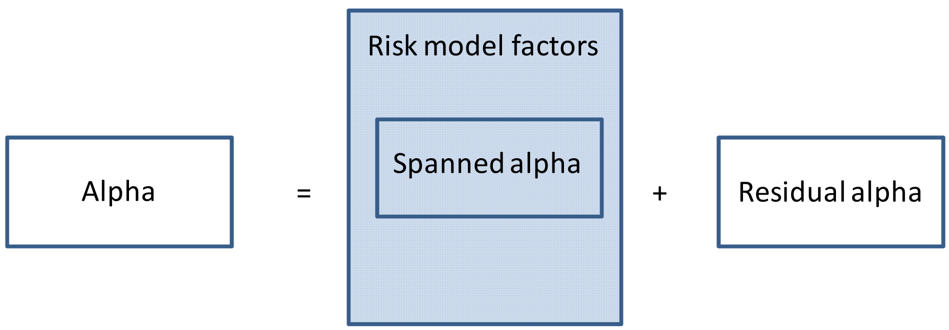
Our naïve benchmark is a simple way of reflecting a portfolio manager's views and information. The weights directly reflect the alphas. If a manager's process for selecting stocks is truly unique, then the correlation between the manager's alphas and those of others is likely to be quite low. Another simple way of building a portfolio based directly on the manager's information is to rank stocks by their alphas, and then long the highest quintile stocks and short those with alphas in the lowest quintile. We examine this as well.

[2] There have been several excellent articles on this topic including Brunnermeier and Pedersen(2009).

Intuition

We can gain some insight into the issue of crowding by understanding how a risk model interacts with alphas in portfolio optimization. Portfolio managers' alphas are often based on asset characteristics that are similar, but not identical to those used to form risk factors. The alphas can be decomposed to a part that is spanned by the risk factors and a part that is *residual* to the risk factors—the *residual alpha.*[3] The spanned alpha is fully captured by the model factors. The residual alpha represents the manager's information that is not in the risk model. This distinction is important, as an optimizer will tend to emphasize the residual alpha because the risk model believes that the residual alpha has no systematic risk (Lee and Stefek (2008)). Figure 1 illustrates the decomposition of alphas into spanned and residual components.

Figure 1: Decomposing alphas.



As we demonstrate below, optimized portfolios can be more or less similar than naïve portfolios. The correlation of the holdings of any two optimized portfolios depends on how the managers' alphas are related to one another and to the factors in the risk model(s) used in the optimization.

If two managers' residual alphas are sufficiently distinct (uncorrelated) and the spanned components are similar, then the holdings of their optimized portfolios will likely *be less correlated* than the alphas. Why? The reason is that the optimizer tends to emphasize the residual alpha – and these are the parts that distinguish the managers. In this case, building portfolios with mean-variance optimization using a single risk model will tend to *decrease* crowding.

Conversely, if two managers' residual alphas are similar, while the portions of the alphas shared by the risk factors are distinct, then the holdings of their optimized portfolios are likely to be *more correlated* than the alphas. This time the residual alpha is the part of the alpha that the managers have in common. When the optimizer emphasizes this component, it increases the similarity of managers' portfolios. In cases like this, using the same risk model in portfolio optimization will tend to *increase* crowding.

We have described the workings of the optimizer in fairly abstract terms. In the following sections, we give some concrete examples of these effects. We also examine whether proprietary models can help mitigate the problem of crowding.

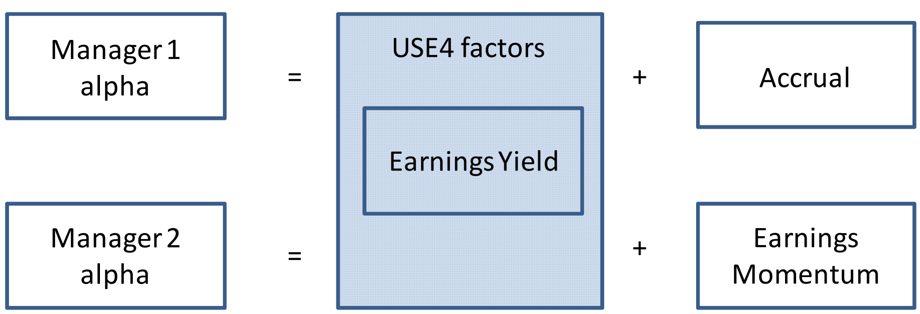
[3] The alpha may be split into spanned and residual parts by regressing the cross section of alphas against the model exposures: $\alpha = X\beta + \varepsilon$. The spanned portion is $X\beta$, and the residual alpha is ε . Note that the spanned alpha is completely captured by the risk model exposures.

Illustrative Cases

We illustrate our findings using two simple cases. In each case, we construct an alpha signal for each of two US equity portfolio managers. As in shown in Figures 2 and 3, each alpha signal is the sum of two components: the first component is spanned by the factors of the risk model, while the second component is not.[4] These polar cases are chosen to illustrate the ideas most clearly.

- **Case 1: Same spanned alpha, but different residual alpha**
  In this case, both managers have earnings-based strategies, but their alphas differ somewhat. One component of both managers' alpha is the earnings yield factor in the Barra US Equity Model (USE4S). This part is spanned by the risk model. However, the second component of the alpha, the residual alpha, is different for each manager. For one manager, it is a proprietary accrual signal, and for the other it is a proprietary earnings momentum signal. This part of the alpha is orthogonal to the factors in the risk model,[5] and it differentiates the managers. The earnings momentum and accrual signals generally have low correlations in exposure and return.[6] Figure 2 illustrates this case.

Figure 2: Residual alphas are less correlated than alphas.



- **Case 2: Same residual alpha, different spanned alphas**
  In this case, each manager bets on different factors in the USE4S risk model: one on momentum and the other on earnings yield. These two factors tend to have low correlation. Both managers bet on accrual which is largely outside the risk model and comprises the residual alpha. As a result, the managers' residual alphas are perfectly correlated. Figure 3 illustrates this case.

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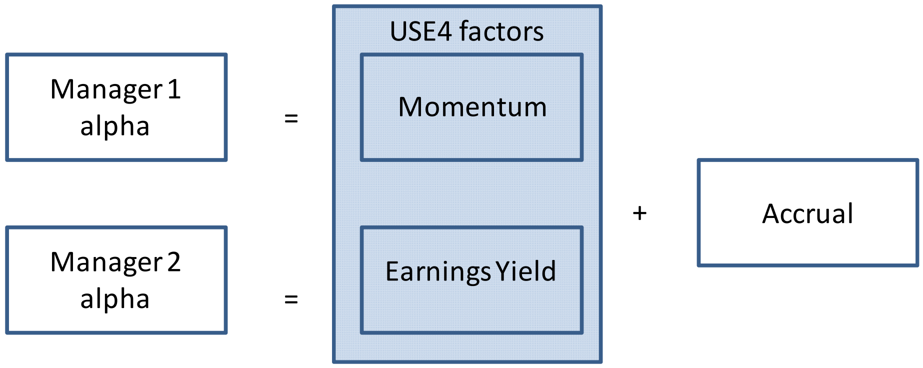
[4] More specifically, the alphas of two managers α_i are constructed as $\alpha_i = w_i\alpha_{iR} + \sqrt{1-w_i^2}\,\alpha_{i\perp}$, where α_{iR} is the manager's spanned alpha, $\alpha_{i\perp}$ is the manager's residual alpha and w_i determines the weight of the two components. The weights are chosen so that the spanned alpha and residual alpha have roughly equivalent strength in the total signal.

[5] These signals largely reside outside the span of the risk factors. However, we further orthogonalized them, so that they are completely outside. We do this for both case 1 and case 2.

[6] For this example, we use the accrual signal from CFRA and the earning momentum signal from the Barra Alphabuilder.

Figure 3: Residual alphas are more correlated than alphas.



Does Using a Standard Risk Model Cause Crowding?

First, we examine whether using optimization causes managers to be more similar than they would be by naively using alphas to form portfolios. For each case, we build a long-short, optimized portfolio for each of the two managers, using the same risk model, the Barra US Equity Model (USE4S). We also form long-short portfolios, whose asset weights are proportional to the manager's alphas, to serve as our naïve benchmarks. Another set of portfolios is constructed by ranking stocks according to their alphas, going long the top quintile and shorting the bottom quintile.[7] To measure crowding, we calculate the correlation between the two managers' optimized portfolio holdings, and the forecast correlation of their portfolio returns.[8] We compute the same measures for the naïve and quintile portfolios.

Table 1: Impact of Optimization on Crowding, December 2009.

	Holding and forecast return correlations	Naive	Q1 - Q5	Optimized long-short with USE4S
Case 1	Holding	0.51	0.47	0.20
	Return	0.90	0.89	0.30
Case 2	Holding	0.57	0.36	0.97
	Return	0.56	0.46	0.90

[7] Stocks within each quintile are equally weighted.

[8] The forecast return correlation for two portfolios with holding vectors h_1 and h_2 and a covariance matrix Σ, is: $\hat{\rho}(r_1, r_2) = \frac{h_1'\Sigma h_2}{(h_1'\Sigma h_1)^{0.5}(h_2'\Sigma h_2)^{0.5}}$

Table 1 shows results of this analysis for the month of December 2009. In the first case, optimizing with the same risk model actually differentiates managers, as shown by both the holdings and the forecast returns correlations. This occurs because the residual alphas of these managers, accrual and earnings momentum, are distinct (i.e., little correlated), and this distinction is emphasized by the optimizer. In the second case, however, optimizing promotes crowding. This happens because the managers' residual alphas are the same, whereas the spanned alphas are different and somewhat negatively correlated. By emphasizing the residual alpha, the optimizer makes the managers' portfolios more alike.

As a check on the robustness of our choice of benchmark, we also compute crowding measures for portfolios formed by going long the top quintile assets and shorting the bottom quintile assets. We see that the holding and return correlations for these portfolios tend to be similar to those of the other naïve portfolios.

Do Proprietary Models Reduce Crowding?

In our examples, the risk model never fully captures a manager's alpha. This is frequently the case in practice, especially when the manager is using a standard risk model. Recently, investment managers have been wrestling with whether they should use proprietary risk models, which include their alpha signals, in portfolio optimization.[9] Two main objectives of creating these models is to produce better risk forecasts and achieve better alignment between the manager's alpha and the optimized portfolio. How well a proprietary model can achieve these objectives for any particular investment process is a broader question and an active area of research.[10]

Our focus here is on a much narrower issue involving proprietary models. Specifically, we ask whether using a proprietary risk model that includes the manager's alpha helps to differentiate a portfolio manager from others, or whether it promotes crowding. To investigate this, we build a proprietary risk model for each manager by adding the manager's residual alpha to the USE4S factor set and re-estimating the model. We build optimized long-short portfolios each month over the period from January 2002 to December 2010. We emphasize that we are not reporting on whether proprietary risk models produce superior risk forecasts or result in improved performance; our focus is solely their effect on crowding.

First, let's see what happens when managers differ in their residual alphas, as in Case 1. Table 2 presents the average results over the period. If both managers use proprietary models, they have less overlap in positions than if they simply form portfolios based on their alphas. However, if both they use the same standard risk model, the overlap is reduced further! Why does using the same risk model achieve more differentiation among managers? The reason is that by incorporating the residual alpha into the risk model, we associate more risk with pursuing it. Therefore, the optimizer does not emphasize these residual alphas – the very source of differentiation among managers—as much when using a proprietary model as it does when using a standard model.

[9] For background Stefek, Lee, and Yao (2012)

[10] It is worth noting that designing, developing and implementing a good proprietary risk model may involve significant costs relative to a standard model.

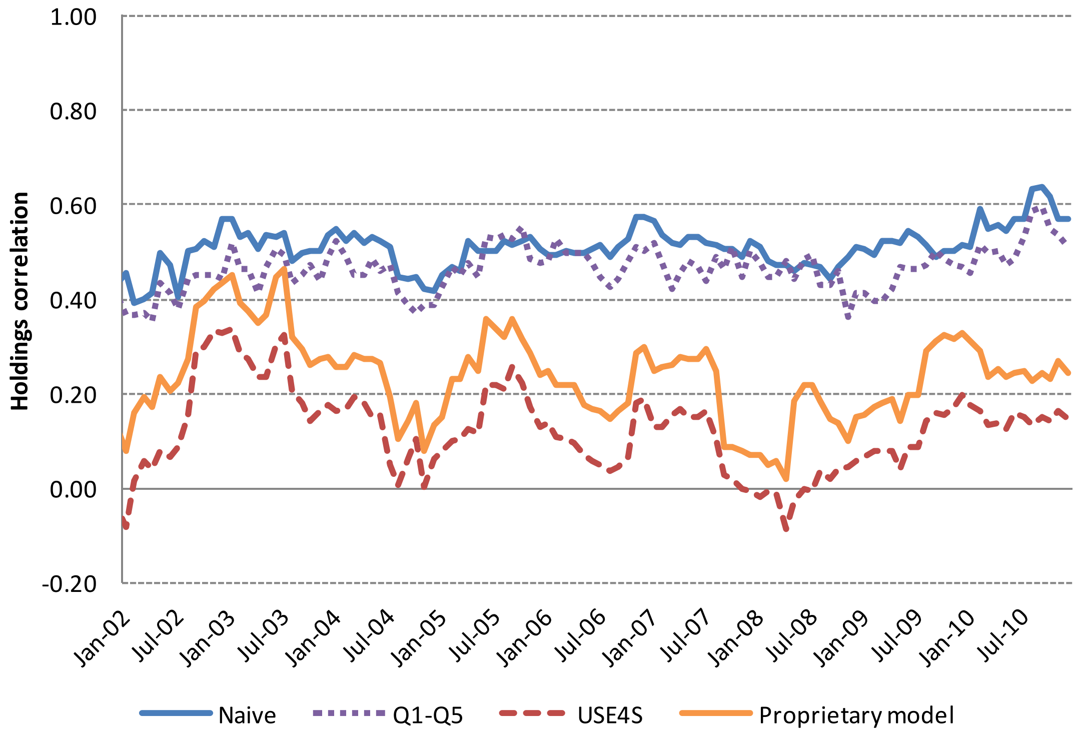
Table 2: Comparing standard and proprietary risk models for long-short portfolios.

	Naive	Q1 - Q5	Optimized long-short	
			USE4S	Proprietary model
Case 1	0.51	0.46	0.12	0.24
Case 2	0.49	0.28	0.96	0.88

Note: average holding correlations are over the period of January 2002 to December 2010

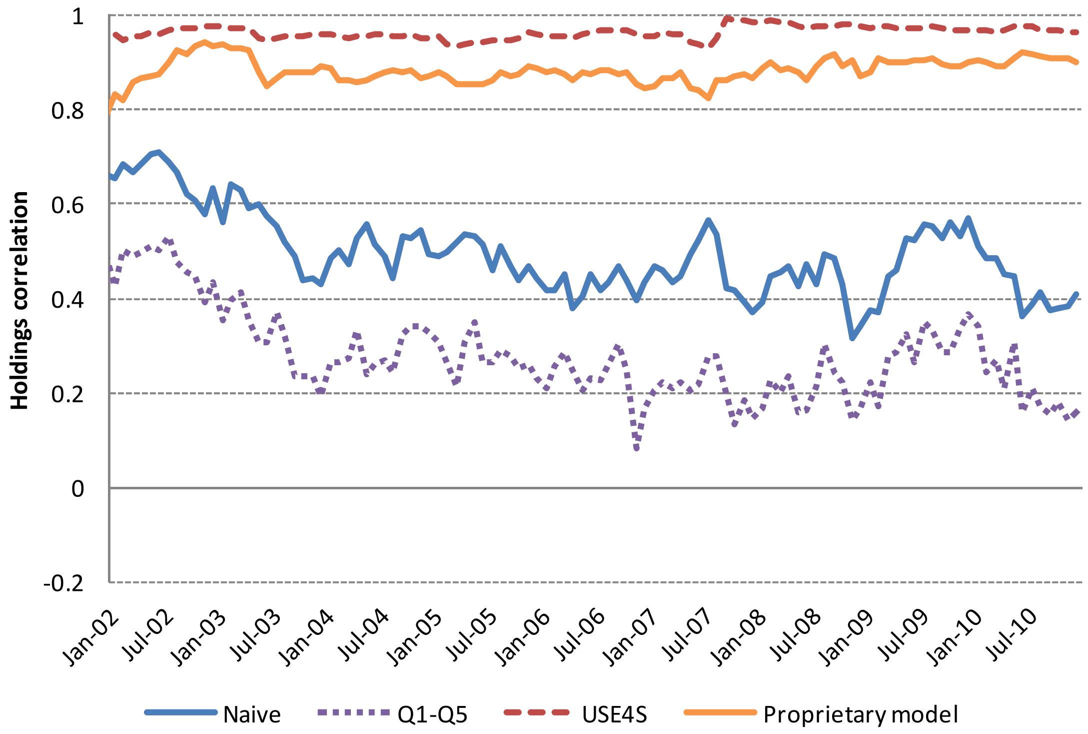
Figure 4 confirms the consistency of these findings through time. Throughout the period, the correlation between the holdings of the optimized portfolios is lower if we use the same standard risk model than if we used proprietary models. The correlations between optimized portfolios do vary over time. Much of that is due to the fact that the correlations between the residual alphas, though generally low, are also not constant over time.

Figure 4: Optimization Differentiates Managers (Case 1).



In the second case, the managers have the same residual alpha, accrual, but bet on different factors in the risk model. Here, the proprietary risk models for both investment processes are the same, since both add the same residual alpha to the standard model. As Table 2 shows, optimization leads to more crowding than constructing portfolios more naively. Furthermore, using the proprietary model results in less overlap than using USE4S does. The reason for this is similar to the earlier case. The proprietary model associates risk with the residual alpha, making the optimizer place less emphasis on the residual alpha – the source of commonality between managers– than risk standard model. Figure 5 shows that these relationships are consistent through time.

Figure 5: Optimization Leads to Crowding (Case 2).



The Impact of Constraints

Thus far, we have focused on unconstrained, long-short portfolios in order to most clearly explain how a risk model used in portfolio optimization can promote or mitigate crowding. However, since institutional investors invariably have constraints on their portfolios, it is natural ask how these constraints affect crowding. While this question is rather broad,[11] we can illustrate the impact that imposing a long-only constraint has in the cases we presented earlier.

To do this, we build optimized, long-only, active portfolios over the same time period as earlier. The benchmark and investment universe are MSCI USA. Often in optimization, the impact of the long-only constraint becomes larger as the target tracking error increases. This is because the optimizer increases the size of the asset positions to take on more risk, causing underweighted assets to hit their lower

[11] When there are constraints, there is an "effective" alpha which , when used in the optimization without the constraints, gives the same optimal portfolio as the constrained problem. The effective alpha is given by $\alpha_{effective} = \alpha - A'\pi$, where A is a matrix of constrains, and π are the dual variables associated with each constraint. To study the broader question, one could start by applying the earlier analysis to managers' effective alphas.

bounds. For this reason, we examine three different active risk targets. Table 3 presents the average holdings correlations over this period.

- **Case 1: Same spanned alpha, but different residual alpha**
  Recall that for long-short portfolios, optimization distinguishes portfolio managers, as demonstrated by the holdings correlations of 12% and 24% for USE4S and the proprietary model, respectively. When we impose a long-only constraint, there is a little less differentiation, as Table 3 shows. The constraint acts against the natural tendency of the optimizer. We also see that using USE4S still produces more manager differentiation than using a proprietary model, though the effect is smaller than in the unconstrained case. The difference in holding correlations between the standard and proprietary models decreases as the target tracking error grows.

Table 3: Crowding in long-only portfolios, Case 1.

Tracking error	USE4S	Proprietary model
1%	0.19	0.27
3%	0.23	0.28
5%	0.21	0.24

Note: average holding correlations are over the period of January 2002 to December 2010

- **Case 2: Same residual alpha, different spanned alphas**
  In the long-short case, optimization leads strongly to crowding, with holdings correlations of 96% and 88% for USE4S and the proprietary model respectively. Imposing the long-only constraint lessens this crowding. Once again, the constraint partially counteracts the tendency of the optimizer. Furthermore, we see there is little difference between using the proprietary model or USE4S.

Table 4: Crowding in long-only portfolios, Case 2.

Tracking error	USE4S	Proprietary model
1%	0.87	0.83
3%	0.78	0.73
5%	0.68	0.66

Note: average holding correlations are over the period of January 2002 to December 2010

What If My Alphas Have No Risk Factor Bets?

Some quantitative managers may feel neglected by our analysis up to this point. These are managers whose alphas are not captured by the risk model at all, including those who deliberately strip away (i.e., neutralize) all risk factor exposures from their alphas. In this case, the manager's alpha is completely residual to the risk model. From our earlier analysis, we might extrapolate that two managers' holdings will be roughly as correlated as the alphas themselves.[12]

But is there anything else about a risk model that could make these manager's more or less similar if they use optimization? One remaining feature of the risk model that may have an effect is its estimate specific risk, the risk model's forecast of the idiosyncratic volatility of a stock.[13] For managers whose alphas are factor-neutral, the optimal asset weight is directly proportional to the alpha but *inversely proportional to the square of its specific risk.*[14] Managers using a standard risk model use the same specific risk estimates to adjust their alphas in arriving at the holdings.

Does using the same specific risk estimates promote crowding? We will not explore this issue further in this paper[15] other than to make one observation. A simple model for unconstrained optimizations shows that when the alphas have little correlation with specific risk, using the standard model has little to no impact of on crowding, on average.

Conclusion

In this paper, we conduct the first rigorous study of the role that a risk model used in portfolio construction has on manager crowding. Contrary to a common suspicion, we show that:

- Using a standard risk model does not invariably lead to manager crowding;
- Using a proprietary risk model that incorporates a manager's alphas may increase or reduce crowding.

Further, we show that the impact of the risk model depends on how the alpha signals are constructed:

- The manager's residual alpha – the information the manager brings beyond what is in the standard risk model – plays a crucial role.
- In particular, if the manager's residual alpha is truly unique, then using a standard risk model in optimization helps differentiate the manager from others, while using a proprietary model may push the manager towards the crowd.

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[12] Foley (2008) suggests that tightly constraining portfolios (or by extension, neutralizing alphas) with respect to risk factors may push managers into a more crowded space.

[13] Specific risk plays a role in determining the holdings of all optimized portfolios.

[14] This is exactly correct for the unconstrained portfolios; constraints complicate this, as usual.

[15] In the general case, we find the result depends on the correlations between the alphas of different managers and the correlation of each set of alphas with the specific risk estimates.

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[1] *As of June 30, 2011, based on eVestment, Lipper and Bloomberg data.*