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Network externalities in mutual funds ☆

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ABSTRACT

The literature on mutual fund flows documents surprisingly large return effects given that mutual fund flows are uninformed (i.e., not related to fundamentals). I provide evidence that network externalities generate the necessary amplification mechanism to support these results. Network externalities are generated by mutual funds with common holdings and return-chasing investors. Economically, I show that the fund flow network externality is 32–92% as large as the typical explanatory effects (e.g., lagged flows). Network externalities generate a 1.5% quarterly excess return that reverses in the subsequent year, and are independent of style investing and robust to multiple specifications of holdings similarity.

Mutual fund flows can significantly impact stock returns. However, these fund flow effects are possible if fund flows are correlated, since a move in a single mutual fund's quarterly fund flows from the 25th to 75th percentile on average accounts for less than 0.5% of a stock's average quarterly volume. In addition, most analyses of fund flows share the underlying assumption that there is (at

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best) no informational content in these flows.[1] How can fund flows be devoid of information and yet persist in a large-scale, non-random pattern to drive economically significant abnormal returns? To generate the economic magnitudes documented in the literature, fund flows need some sort of propagation mechanism.

I provide evidence that the propagation mechanism of fund flows is rooted in network externalities generated by return-chasing investors in mutual funds with similar holdings. These reinforcing network externalities can amplify relatively minimal correlated flows to the levels documented in the literature. As an illustration, assume that funds A and B get inflows, with which they each buy their own (similar) portfolio. Those jointly held stocks appreciate (modestly), which generates a similar effect for funds C, D, and E holding those similar stocks. These three funds, due to return-chasing, get inflows, which repeats the process, benefitting all funds, who in turn get more inflows, reinforcing the process. This process iterates over days or weeks, thus aggregating to the documented monthly or quarterly effects. I refer to this process as a "network externality" and it is the subject of this study.

This mechanism is a form of positive feedback trading, but among mutual funds. The key insight, however, is that the investors engaging in this positive feedback trading do not necessarily know they are doing so.[2] From a single investor's point of view, he is investing in a mutual fund, which subsequently appreciates, validating his wise investment. Gervais and Odean (2001) have shown that this type of positive feedback reinforces overconfidence rather than prudent behavior. Campbell, Ramadorai, and Ranish (2014) show that past success reinforces a repetition of (possibly less-than-rational) behavior. Since there is no easy way to value a mutual fund (apart from individually valuing all the holdings and aggregating), it may be difficult to identify when the mutual fund is overvalued, thus limiting arbitrage (Stein, 2009). Rational arbitrageurs may even step in to engage in positive feedback trading themselves (DeLong, Shleifer, Summers, and Waldmann, 1990).

Network externalities among mutual funds are meaningful. Extant studies of fund flow effects (e.g., Coval and Stafford, 2007; Lou, 2012) use lagged flows as the primary predictor variable. I find that network externalities are 32–92% as large as these primary flow effects on average. Additionally, the distribution of effects is skewed: above the 75th percentile, the network externality is many multiples of the original shock. I also find network externalities associated with abnormal mutual fund returns of 1.5% in quarterly alpha, which substantially reverse in the subsequent year, consistent with the literature (Zheng, 1999; Frazzini and Lamont, 2008; Lou, 2012).

Measuring network externalities in mutual funds has not been possible due to difficulties in identification. Ideally, one would measure events separated by space and time to identify a sequential effect. Unfortunately, such a separation is not possible with mutual fund data, since this type of mutual fund dynamic is best measured at a daily frequency (Edelen and Warner, 2001; Bollen and Busse, 2001, 2004).[3] While returns are available at a daily frequency, mutual fund holdings data (and thus the measurement of similarity) are only available quarterly. Quarterly data treats daily dynamics as occurring contemporaneously, and so confounds an externality with an exogenous correlated shock.

To addresses this identification problem, I take a network-based approach that is designed to address the contemporaneous measurement of externalities. This approach applies a two-step generalized method of moments (GMM) estimation typically used to identify peer effects in social networks (Kelejian and Prucha, 1998). First, I form a network of mutual funds connected by common holdings. Second, I subtract average net flows from each fund's own flows to create a centered measure. Third, I exploit the network structure to obtain instruments for use in the GMM estimation. In the final step, I re-estimate the model, but with the predicted fund flows from the previous

[1] For example, the "dumb money" result of Frazzini and Lamont (2008). Khan, Kogan, and Serafeim (2012) use fund flows as an instrument for overpriced stocks since flows are assumed unrelated to firm fundamentals. Greenwood and Thesmar (2011) call fund flows "non-fundamental."

[2] These could plausibly be the positive-feedback trading noise traders in DeLong, Shleifer, Summers, and Waldmann (1990).

[3] These studies show that performance persistence and market timing are present for mutual funds, but must be measured at a daily frequency. This is the only result showing performance persistent among mutual funds (to my knowledge) that has not since been contested with an opposing result.