The interconnectedness risk factor: extending the systematic risk beyond market risk

Michail Vamvakaris*† George Wang‡

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Abstract

Interdependencies between securities within financial markets are modelled as a graph and we introduce the interconnectedness risk factor, peripheral-minus-central (pmc), that relates the centrality of an asset to its exposure to systematic risk and its expected returns. We show that the proposed factor is statistically significant explaining cross-sectional variation of returns of centrality-sorted portfolios when included in well-studied asset pricing models. Evidence show that the interconnectedness factor is priced in the 25 size-value double sorted portfolios and the 12 industrial portfolios. Our analysis also provides new insights for the betting-against-beta (BAB) factor.

*School of Computer Science, University of Manchester, e-mail: michail.vamvakaris@manchester.ac.uk

†Barings LLC, e-mail: michail.vamvakaris@barings.com

‡Department of Accounting and Finance, Lancaster University Management School, e-mail: george.wang@lancaster.ac.uk

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1 Introduction

An assumption of the Capital Asset Pricing Model (CAPM), which is introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966), is that two assets are related to each other proportionally to their individual exposure to the market factor. In reality though, companies are related to each other through numerous channels, mainly via trade flows where companies establish a supplier-client relationship or via direct and indirect investments and synergies or strategic alliances. Under these circumstances, companies form a network of inter-dependencies where positive and negative shocks propagate among the interacting elements. These interactions add another dimension in the perception of risk exposure and empirical evidence suggests that the risk associated with the interconnected nature of businesses is considered as part of the idiosyncratic risk of a company. [1]

Chen (2014) introduces the notion of the *network risk* that quantifies the exposure of each asset to its closely associated assets. The network risk is argued to be part of the idiosyncratic risk of a security and *stocks are compensated for risk that arises from shocks to networks that contain them*. Peralta and Zareei (2016) analyse correlation-based equity networks and provide evidence that the position of an asset in the associated financial network is related to its exposure to market risk. They also introduce a portfolio selection strategy based on the structural properties of the constructed temporal networks. According to Eom et al. (2006), assets having a higher number of connections in the correlation-based network have an intimate relation with the market factor while assets with a small number of connection have a weaker relation.

Our contribution is to present the Interconnectedness Risk (IR), which adds a new dimension to risk modelling and to examine to which extent the interconnectedness risk is indeed a priced risk factor in the financial markets. Being inspired by Pozzi et al. (2013), we present a composite Centrality Index (CI) which captures the importance of a security within a financial network considering various centrality measures, local and global, fact that enables a holistic quantification to network risk. In section 3 we present the economic intuition underlying each centrality measure composing the proposed CI. Our arguments support the idea that the CI measures the systematic importance of an asset and quantifies the influence of a security in the financial ecosystem. Fig 1, is a graphical illustration of our contribution.

Allocating securities in 10 equally-weighted centrality-sorted portfolios based on the Centrality Index, we show that there are properties such as volatility, liquidity, book-to-market ratio etc that appear to be related with the position of an asset in the associated financial network. Empirical evidence shows that returns of a portfolio (raw and risk adjusted returns) are increasing monotonically as we consider portfolios including less central securities. Earlier work by Pozzi et al. (2013), Peralta and Zareei (2016) and Ramirez (2017) support our proposition that peripheral assets are those receiving a risk premium, even though the work of Chen (2014) provides evidence that central assets are those awarded with risk premium.

In addition, the Diversification Index (eq. 7) quantifies the degree of diversification within a portfolio. Using the Diversification Index we show that the portfolio containing the most central assets is highly concentrated in contrast to the portfolio containing the most peripheral assets that is highly diversified. This result reveals the strong exposure of central asset to systematic risk, compared to peripheral assets that display a much lower exposure.[2] Our results provide a reasonable explanation of earlier findings presented by Peralta and Zareei (2016) and Onnela et al. (2002). Both papers show that peripheral assets are those receiving a non-zero weight in the optimal minimum variance portfolio.

By obtaining a short position on the central portfolio and a long position on the peripheral portfolio we create the Peripheral-minus-Central (pmc) portfolio that is found to capture the Interconnectedness risk. We argue that the pmc factor portfolio is not related to the idiosyncratic risk as supported by other researchers but rather we propose that it is an aspect of systematic risk of an asset that is currently overseen. The phrase "too big to fail" referring to the size risk is

[1] Ramirez (2017) modelled inter-dependencies between companies in US through the lenses of a supply chain networks and he argues that these inter-dependencies are part of the idiosyncratic risk a business and cannot be eliminated.

[2] Markowitz (1952) argues that in well-diversified portfolio the idiosyncratic risk of individual companies vanishes and the portfolio holds an exposure to systematic risk only.

interpreted as "too interconnected to fail" in the context of financial network. Peripheral securities receive a risk premium due to the associated risk of not being well-connected in the network.

The pmc portfolio is found to be statistically significant when used as independent variable (risk factor) in well-studied asset pricing models including the CAPM model, the three factor Fama and French (1993) model, the five factor Fama and French (2015) model, the four factor Carhart (1997) model, the four factor liquidity Pástor and Stambaugh (2003) model etc., aiming to capture the cross-sectional variation of returns of the portfolios being formed based on the Centrality Index. We provide evidence that the pmc factor remains statistically significant when used against out-of-sample data such as the 5-by-5 double-sorted size-value portfolios proposed by Fama and French as well as the 12 Industrial portfolios proposed by the same authors.

Noteworthy, we show that the proposed risk factor has a significant contribution to capturing cross-sectional return variation of the betting-against-beta (bab) factor portfolio. The interconnectedness risk factor provides a sensible explanation of the pricing anomaly phenomenon presented by Frazzini and Pedersen (2014). Returns of the peripheral assets in the network display a low degree of correlation with the other assets in the market, and thus we observe a significantly lower market beta. We show that peripheral assets are characterised by low capitalisation, low liquidity and high book-to-market ration.

The rest of the paper is structured as follows: Section 2 covers related literature review in the intersection between financial analysis and graph theory, Section 3 provides an intuition underlying the graph based analysis of financial markets, Section 4 is dedicated to presenting the data used in the context of our empirical analysis, Section 5 covers the technical details of our proposed approach, Section 6 presents the results and findings and Section 7 contains the conclusion and a short discussion.

2 Literature Review

In the recent financial literature, academics have presented numerous applications of graph theory in financial analysis. Bonanno et al. (2003) conducted an empirical analysis based on graph theory aiming to test the validity of CAPM in financial markets. They compare the topological properties of a financial network constructed based on correlation of the actual historic returns of securities with the corresponding financial network constructed based on the expected return series under the CAPM. Results indicate that the network constructed based on expected return series is not similar to the original network, providing evidence that the CAPM cannot capture adequately cross-sectional variation of returns.

Eom et al. (2007) present an extension of earlier work being published by Bonanno et al. (2003). Using the Arbitrage Pricing Model (APM) instead of the CAPM model, they show that the higher the number of factors included in the asset pricing model estimating expected returns, the closer the simulated network is to the real network implying that the market factor is not a stand-alone factor for explaining return variation. They also provide evidence that assets with exposure to common factors tend to form clusters implying that inter-dependencies among assets go beyond the limits of their individual exposure to the market factor.

Pozzi et al. (2013) analyse financial networks constructed based on the exponential smoothing correlation of return series of assets being traded in the American Stock Exchange (AMEX). They provided evidence that the portfolio including the n most peripheral stocks, where $n \in \{5, 10, 20, 30\}$, outperforms the equal-size portfolio including the most central securities in terms of risk-adjusted returns. This phenomenon was attributed to the diversification achieved in the peripheral portfolio as opposed to the high concentration on the central portfolio.

Baitinger and Papenbrock (2016) include a small number of fixed income, commodities, currencies and alternative investments in their analysis. They relate the weight allocated to each security in an optimal portfolio with its position in the financial graph with more central assets being allocated smaller weights and some central assets receiving even negative weights indicating a short position. Nonetheless, authors do not apply short-selling as part of their investment strategy since *these investment strategies can exhibit undesirable portfolio weights concentrations.*

Peralta and Zareei (2016) analyse correlation based networks including 200 assets with the highest capitalisation among the constituents of the S&P 500 index. They provide evidence that the importance of an asset in the associated financial network is related to its exposure to market risk measured by the market beta (β_{mkt}). Furthermore, they prove that there is a negative relationship between centrality of a security and the magnitude of the corresponding optimal weight allocated in the minimum variance portfolio Markowitz (1952), validating earlier empirical results being presented by Onnela et al. (2002). They introduce a portfolio selection strategy based on the structural properties of the constructed temporal networks. They identify regime shifts using attributes of the network structure and the proposed strategy switches between investing on the most central and the most peripheral securities according to the prevailing circumstances, forming a buy and hold strategy.

According to Eom et al. (2006), there are stocks displaying a strong relationship with other stocks within a financial market, obtaining an important and vital role within the financial ecosystem, while other securities remain less "active". Using historic data for securities being included in the S&P 500 and the KOSPI indexes, authors construct correlation-based financial networks. They show that assets having a higher number of connections in the network have an intimate relation with the market while assets with a small number of connection have a weaker relation. This phenomenon implies that the position of an asset in the financial network is related to its individual exposure to the market risk.

Focusing on applications of graph theory in economic data, Ahern (2013) examines how the centrality of an industry in the associated industry-based network determines the expected returns for assets belonging to a specific industry. Constructing graphs using data from the Input-Output tables from the U.S. Bureau of Economic Analysis (BEA) he concludes that stocks belonging to central industries outperform those belonging to peripheral industries. Central industries reward investors with a risk premium due to increased risk of a shock propagation towards central industries. The author concludes that the proposed factor, which is created by buying stocks belonging to central industries and selling those belonging to peripheral industries, acts as a proxy of unknown factors or as a substitute to the market risk. Nevertheless, the proposed factor is not statistically significant on explaining cross-sectional return variation when tested against out-of-sample portfolios such as the 5-by-5 double-sorted size-value portfolios proposed by Fama and French.

Ramirez (2017) conducts an empirical study of the trade network in USA aiming to understand to which extent the importance of a node in the trade network is related to variations in asset returns in financial markets. The presented argument supports the idea that the supply chain network is part of the idiosyncratic risk of a company and findings indicate that peripheral firms are awarded with a risk premium because of the higher degree of idiosyncratic risk they inherit due to their undiversified supply chain network.

Aobdia et al. (2014) studies industrial networks using data related to the real economy and they find a relationship between expected performance of various industries and the corresponding centrality in the associated network. They reveal that the position of an industry in the network is related to its exposure to economic shocks and they provide evidence that central industries receive a higher levels of aggregated risk because of their exposure to the systematic risk.

More recently, Richmond (2019) studied the relationship that links the centrality of a country in the global trade network with the interest rates and the currency risk premium. Results suggest that countries obtaining a central position in the trade network have lower interest rates and currency premium and that the growth of the consumption of the central countries co-varies more with the world consumption growth compared to peripheral ones. This finding adds more evidence in the existing literature by illustrating the relation between centrality and exposure to systematic risk even though their analysis is focused on networks of different nature compared to the literature presented so far.

Rossi et al. (2018) study financial networks of fund managers and create a connection between the position that a manager possesses in the associated social network that portfolio managers form with the performance of various portfolios. They conclude that a greater number of connections that each manager maintains in the network is related to better performance for its managing portfolios.

In the following section, we present the intuition underlying our approach and the economic interpretation of the network. In addition, we provide the technical details for the construction of the correlation-based networks used as part of our analysis.

3 Intuition and economic interpretation of the network structure

This section aims to provide readers the economic intuition of financial networks. We explain the information that a financial network preserves and the reasoning underlying our analysis.

The present work studies correlation-based networks meaning that networks are constructed based on the Pearson correlation, $\rho_{i,j}$, of historic return series of pairs $\{i, j\}$ of stocks being traded in the US stock exchange markets. Every security included in the sample becomes a node in the associated financial network and an edge connecting a pair of nodes has a weight proportional to the correlation of historical returns.

We should highlight that similarity between stocks is only based on investors perspective and the information captured by the price series. In our work similarity is not calculated based on the true nature of business, even though under the efficient market hypothesis prices are assumed to depict this piece information. Similarity networks based on the true nature of the business have been proposed by Hoberg and Phillips (2016) where similarity among the offered products of companies is considered and information is extracted using text-mining techniques on product descriptions.

Starting with n assets, we calculate a correlation matrix $C \in \mathbb{R}^{n*n}$ of historic returns. Correlation is a measure of similarity with higher values indicating more similarly behaving assets. The notion of centrality though, as explained later, is strongly related to that of distance so, we transform correlation $\rho_{i,j}$ to another metric $d_{i,j}$ which defines a distance between elements i and j as a function of correlation. Pozzi et al. (2013) suggest an appropriate measure of distance between financial assets the formula

$$d_{i,j} = \sqrt{2(1 - \rho_{i,j})}, \tag{1}$$

which implies that, $d_{i,j} = 2$ when $\rho_{i,j} = -1$ and $d_{i,j} = 0$ when $\rho_{i,j} = +1$. Smaller values of distance $d_{i,j}$ indicate a higher level of similarity given that the distance $d_{i,j}$ decreases monotonically as correlation increases. Thus, the correlation matrix C is transformed into a distance matrix D.

Note that the original correlation matrix C consists mainly of non-zero elements, where the majority of entries is statistically significant, yet economically insignificant. Let us consider two assets i and j with statistically significant correlation $\rho_{i,j} = 0.08$. We postulate that, economically speaking, the majority of investors would treat those assets as uncorrelated.

Consequently, weak relationships between assets should be filtered out. We are interested in maintaining only the backbone of the financial network that preserves important information i.e. edges connecting distant nodes should be removed and only those connecting closely related ones are maintained. In order to remove edges with large weights, the Minimum Spanning Tree (MST) algorithm is used, introduced first by Mantegna (1999) in the context of financial network analysis.

The matrix D initially contains at maximum $\frac{n(n-1)}{2}$ non-zero elements indicating edges connecting every pair of assets in the network. Recall that the elements of main diagonal of matrix D are zeros. As part of the filtration process, we aim to maintain only $n - 1$ edges with the smallest weights such that the resulting graph is a tree i.e. no loops are allowed. Loosely speaking, this equals to connecting each security only to its closest counterpart given that the tree structure is preserved. The *filtered* matrix D, where the weak relations have been replaced with value zero, is the adjacency matrix of the financial networks used in the context of this work. For those not familiar with terminology on graph theory, adjacency matrix is a square matrix containing information about the connections within a graph.

As mentioned earlier, Eom et al. (2006) observed that securities in the financial networks do not display the same number of relationships with other assets. A similar finding is reported in the present work where, in the filtered network, some assets are found to be the closest counterpart for numerous assets, while others are only connected to a small number of similar assets.

Thus, nodes can be classified into groups depending on the number and the strength of their connections. An extreme case includes nodes that present a high degree of similarity with numerous nodes meaning that the number of edges preserved in the filtered network is high and weights are small. A second extreme case includes nodes which are related only to one node and the corresponding weight is large i.e. low similarity. In-between the two extreme cases we identify nodes that present low similarity with numerous nodes, nodes that present high similarity with only a small number of nodes as well as nodes having a mixture of strong and weak edges. A similar categorisation is presented by Di Matteo et al. (2010).

The first extreme case denotes "herding" among securities where assets strongly connected to a common neighbour display high correlation among their return series. Even though the filtering process eliminates numerous edges, common sense dictates that assets that are highly correlated with a specific asset i in the financial network, are also expected to be correlated to each other. Eom et al. (2007) found that well-connected nodes in the financial network are closely related with the performance of the market.

Assets belonging to the latter extreme case display a "unique" behaviour since the patterns presented in returns series are not closely related to that of other assets. This group includes assets displaying an independent, if not contrarian, performance compared to the other elements of the network and investors perceive them as if they differ from the other assets. The other two categories are mainly by-products of the two extreme cases.

The network representation of the financial markets is a tool for studying the quality and strength of interactions among the elements within the market. Assets displaying a "unique" behaviour are only weakly connected with the rest of the network and a shock being originated on these entities is considerably less probably to propagate in the network meaning that these assets hold a systematically unimportant position in the market. On the other hand, nodes displaying high similarity to numerous other nodes are more tightly connected with the other elements of the financial market. The performance of highly connected nodes has an immediate effect on the performance of numerous other securities. A shock being originated in highly connected nodes would immediately affect other securities of the markets and the shock would soon propagate through the network.

The various centrality measures proposed in literature offer a quantitative metric for measuring the importance of a node within a network and characterizing the quality of connections among nodes. Each centrality measure captures a different aspect of importance regarding the interaction of each element with the other entities.

According to a research paper published by International Monetary Fund, Chan-Lau (2018):

> "(...) market-based financial networks typically associate the systematic importance of a firm or node with its centrality."

This statement appears to be a reasonable explanation for Onnela et al. (2002) and Peralta and Zareei (2016) finding that peripheral securities should be included in the minimum variance Markowitz portfolio. Idiosyncratic risk is eliminated with diversification, yet systematic risk does not, and consequently, investing in assets with low exposure to systematic risk leads to minimum variance. Ahern (2013) also relates centrality with exposure to systematic risk by highlighting the fact that industries that belong to the centre of the industrial networks inherit increased levels of systematic risk.

The rest of this section provides the economic interpretation of various centrality measures that are used in the context of the present research.

The most intuitive centrality measure is *Closeness* centrality which measures the topological centrality of a node at a global scale. The position of a node in the associated network under the closeness centrality is defined relative to its average distance to every other node in the network.

According to Bavelas (1950) closeness centrality is defined as:

$$CC(x) = \frac{1}{\sum_y d_{x,y}} \tag{2}$$

where $CC(x)$ is the closeness centrality score calculated for node x and y refers to any other node in the network. Higher score of closeness centrality indicates a more central, topologically speaking, position in the network. Assets characterized as peripheral according to closeness centrality are those whose price tend to fluctuate in a more independent manner. In contrast, central securities are those whose returns series are on average closest to any other asset in the network, or in other words the central nodes are those following, or creating, the prevailing trends in the market. Findings presented later in this paper support the idea that central nodes are those creating the trends.

Betweenness centrality is associated with the notion of random shock propagation within the network and the influential role that a security possesses in the financial market. It measures how many shortest paths connecting every pair of nodes i and j come through a specific node x. Each path corresponds to a channel which allows the propagation of a random shock, since we expect that if asset i and j are strongly positively correlated then, any unexpected event involving asset i is foreseeable to have a direct impact on asset j. Thus, we can infer that the higher the value of the betweenness score the more probable is for an asset to be affected by a shock being originated by any other asset in the network. The reverse is also true, implying that any shock being originated on asset i with a high betweenness centrality would be propagated to other assets in a faster pace in comparison to a shock being originated by a low betweenness centrality asset.

According to Freeman (1977) betweenness centrality is defined as:

$$BC(x) = \sum_{x \neq i \neq j} \frac{\sigma_{i,j}(x)}{\sigma_{i,j}}, \tag{3}$$

where x is a node whose centrality score is calculated, i and j are any pairs of nodes in the network, $\sigma_{i,j}(x)$ is the number of shortest path connecting nodes i and j including node x and $\sigma_{i,j}$ is the total number of shortest path connecting nodes i and j.

This fact became obvious in the crisis of 2008 when a shock originated in the financial sector soon propagated into the entire market. The central position of the financial industry was revealed by Kenett et al. (2010), yet similar results have been referred by others researchers.

Strength Centrality measures the intensity of local dynamics and interactions of a security with its immediately related ones.

Mathematically speaking strength centrality is defined:

$$ST(x) = \sum_{y \in N_x} d_{x,y} \tag{4}$$

where x is the node whose centrality score is calculated, and N_x is a subset of the network including only nodes adjacent to node x. This centrality is directly related to the exposure of a security to the systematic risk, since strength centrality is a quantification of how strongly connected each component of the network is with the other elements of the network.

In the next section we provide the technical details of how the aforementioned centrality measures are combined into a single Centrality Index which is then used in the portfolio selection process.

4 Capturing Interconnectedness Risk (IR)

Aiming to quantify the contribution of a risk factor in asset return variation and the corresponding risk premium, common practice in financial literature is to create factor-sorted portfolios by sorting securities based on the individual exposure to the factor under study. In the context of this work, we sort securities based on the interconnectedness risk (IR) measured by the Centrality Index (eq. 6). Then, 10 equally-weighted centrality-sorted portfolios are selected such that the first decile of the ranking forms the Portfolio1 and the last decile forms Portfolio10.

A buy-and-hold investment strategy is applied on centrality-sorted portfolios with annual rebalance. Portfolio selection process takes place at the first trading day of each calendar year (t). Daily returns for the year prior to portfolio selection (t-1) are used in order to construct the associated correlation-based network.

Before forming the centrality-sorted portfolio though, we should first select which securities are considered as investment universe for a given year (t). Thus, a security should fulfill specific criteria before considered as an investment opportunity. These criteria are essential for preventing us from including in our portfolios assets with abnormal behaviour, fact that is expected to lead to spurious and inconsistent results.

Even though the U.S. Securities and Exchange Commission (SEC) defines a *penny stock* as an asset being traded below 5$, individual traders have their own definition. Using the definition presented by Tortoriello (2009) as well as numerous other researchers when developing investment strategies, in the present work a penny stock is defined as an security traded at a price less than 2$. Portfolios are constructed at the opening of the market at the first trading day of each year and a security should have a minimum opening price of 2$ in order to be included in the investment set.

Additionally, assets should be listed in a stock exchange for at least one year before being considered as an investment opportunity. This ensures that companies fulfil the standards set by individual stock exchanges for an significant period. However, for various reasons, trading on specific assets might be revoked temporarily. Thus, an asset is not considered as an investment opportunity if price information is not available for more 10 days over the previous year. Days were the activity of the stock markets is recalled do not count as missing data.

The third criterion is imposed by the need to accurately estimate the Pearson correlation between a pair of securities. By definition, the Pearson correlation is calculated as

$$\rho_{i,j} = \frac{cov(i,j)}{\sigma_i \sigma_j}. \tag{5}$$

This implies that if $cov(i,j) = 0$, then $\rho_{i,j} = 0$, yet in case that $\sigma_i = 0$ or $\sigma_j = 0$, then $\rho_{i,j}$ is undefined. If an asset included in the investment sample has returns with zero variability over the previous year i.e. a stock whose returns are all equal to zero, then it is not possible to construct a connected network since no edge would link this asset with any other asset in the financial network. To accommodate an accurate estimation of the correlation matrix highly illiquid assets are excluded and an asset should have at least 60 non-zero recorded returns over the previous year. We admit, though, that 60 is an arbitrary number, yet experimenting with various values does not affect presented results.

Eligible securities form the investment universe for year t, and the associated financial network is constructed using the process explained on Section 3. Based on the constructed network, each centrality measure ($BC(x)$, $CC(x)$ and $ST(x)$) is calculated independently for every security in the network. For each centrality measure, securities are ranked with central securities obtaining a higher position in the corresponding ranking. Afterwards, the *Centrality Index* (eq. 6) is calculated aiming to create a single measure of centrality that captures the centrality ranking of a security.

The Centrality Index is, in fact, the normalized average ranking of an asset in the three centrality measures defined in earlier section. The formula for calculating the Centrality Index is

$$CI(x) = \frac{BC(x)_{rank} + CC(x)_{rank} + ST(x)_{rank} - 3}{3 * (n-1)} \tag{6}$$

where $CI(x)$ is the normalized average centrality ranking of security x and $0 < CI(x) < 1$ with values closer to zero signifying a more central position in the network, $BC(x)_{rank} \in 1, 2, 3, ..., n$ denotes the position that a security x obtained when securities are ranked based on Betweenness Centrality and similarly $CC(x)_{rank}$ and $ST(x)_{rank}$ denote the corresponding ranking position for the Closeness Centrality and Strength Centrality.

The Centrality Index is the criterion based on which assets are sorted before being assigned to different centrality-sorted portfolios. The aforementioned approach of forming centrality-sorted portfolios is repeated over the period $1981 - 2018$. The next section elaborates on the data set used in the context of this analysis.

5 Data Description

For the purpose of the present analysis we used data retrieved from the Center for Research in Security Prices (CRSP), maintained by Wharton Research Data Services (2019). Additional data sets are obtained from Pastor L. (2019) and Kenneth French (2019).

5.1 Security Data

Data regarding securities is provided by the CRSP database and includes daily data covering the period from 2^{nd} January 1980 till 31^{st} December 2018. The data set contains nominal security prices, price returns, price returns including dividends, delisting returns, split-adjusted prices, number of outstanding shares and trading volume for each individual security (identified by the unique PERMNO assigned by CRSP database) quoted in the NYSE, AMEX and NASDAQ, with share codes 10 or 11. The data set includes 21603 securities for a total of 9835 trading days covering a period of 39 years.

Even though it is common practice in financial community to validate a model using monthly returns, we notice an unexpected inconsistency in the data. The annual cumulative returns are not equal when calculated based on monthly and daily returns for specific assets. The issue is raised by the fact that monthly returns are reported as *Not Available (NA)* when a large portion of daily returns are reported as *Not Available (NA)* for the same month, which leads inevitably to inconsistencies. For this reason, only daily data used for our analysis, yet for comparison purposes we report results based on monthly returns which are calculated as cumulative daily returns.

In addition, in cases where securities undergone a split or reverse-split operation, the return at the first date when trading is resumed is missing rather than calculating the return with respect to the latest available report. To overcome this issue, we use the split- and dividend- adjusted daily prices in order to calculate the missing return.

5.2 Factor Data

Monthly data for the performance of the market, size, value, operational profitability and investment style factor as proposed initially by Fama and French (1993) and Fama and French (2015) are provided by the Kenneth French's website. Similarly, monthly data related to the momentum factor portfolio as described in Carhart (1997) are obtained from the CRSP database while monthly data for the traded liquidity factor are obtained from Pastor L. (2019). Data regarding the betting-against-bets factor portfolio are obtained from the data library offered by the AQR global investment management firm. Monthly data cover the period January 1980 to December 2018.

5.3 25 size/value portfolios and Industrial portfolios

Monthly data for the 25 double-sorted size/value portfolios as originally presented by Fama and French (1993) are obtained from the CRSP database and data relevant to the monthly performance of the 12 Industrial portfolios proposed by the same authors as obtained from Kenneth French's website.

6 Empirical analysis and results

Modern Portfolio Theory dictates that investors are rewarded with a risk premium that is proportional to their exposure to risk. Investor holding an exposure to undiversifiable risks only, such as market risk, are only rewarded with the basic risk-free rate. Empirical results have exemplify the presence of numerous risk factors, and investors are rewarded additional returns when their investments are exposed to the corresponding sources of risk. It is important to note that every risk factor offers a different risk premium.

The main focus of this work is to provide evidence that the interconnectedness risk is a priced factor in the equity markets in US and that investors receive a risk premium for investing in securities with an exposure to this factor.

In this section, we present performance statistics for the centrality-sorted portfolios and we provide evidence supporting the argument that the position of a security in the associated financial network is related to its expected returns. Using various asset pricing models we aim to shed light on the source of the cross-sectional return variation and the risk exposure of the aforementioned investment portfolios. We then, illustrate that the model best explaining variation of the cross-sectional returns of the centrality-sorted portfolios is consistent throughout time and that exposure to proposed risk factor is neither temporal nor conditional to prevailing circumstances in the market. The interconnectedness risk factor is found to a priced risk factor on out-of-sample portfolios constructed without an explicit exposure to this factor. Finally, we provide a sensible explanation for the predictive power of the proposed risk factor for the well documented low beta price anomaly, the betting-against-the-beta (bab) factor.

6.1 Performance of centrality-sorted Portfolios

Previously we explained the process for constructing the centrality-sorted portfolios. Applying a buy-and-hold strategy with annual rebalancing from 01/1981 till 12/2018 results in 456 monthly returns for the 10 investment portfolios.

Table 1 reports the average monthly return $\bar{r}_p$, the standard deviation of returns $\sigma(r_p)$ and the Sharpe ration $(\bar{r}_p - rf)/\sigma(r_p)$ for the 10 centrality-sorted portfolios, where rf is the risk free rate. Portfolio 10-1 in Table 1 indicates a portfolio that holds a long position on the peripheral portfolio and a short position on the central portfolio. We observe that average returns and the Sharpe ratio have a positive relationship with centrality and there is a negative relationship between standard deviation of returns and centrality. Portfolio 10 is the least volatile among the portfolios. Portfolios including peripheral assets i.e. those with a higher Centrality Index, tend to outperform their central counterparts. Portfolio P10 compensates investors more than twice compared to portfolio P1 for every unit of risk. In Table 1, the t-statistics corresponds to the t-test for the mean with the null hypothesis $H_0 : \mu = 0$ and $H_1 : \mu \neq 0$, where μ is the mean return of a portfolio for the period under study. The t-test is applied to the portfolio returns after subtracting the risk-free rate.

Although in some cases average returns of consecutive portfolios with respect to the centrality of the assets included are similar (see P7 and P8), the aggregated differences add up to a statistically significant difference when considering the performance of the central (P1) and peripheral (P10) portfolios. The Wilcoxon signed-rank test (Wilcoxon (1945)), which is a non-parametric hypothesis test with the null hypothesis being that two samples are drawn from the same distribution, is also used for testing the statistical significance of the difference between the realised returns of the central (P1) and peripheral portfolio (P10). The aforementioned hypothesis test is recruited given evidence provided by Peiró (1994) that stock returns are not normally distributed. The p-value of the Wilcoxon test is $p = 0.0001$ which leads to the rejection of the H_o and consequently, the difference in performance between the two portfolios is statistically significant.

Aiming to reveal the idiosyncratic characteristics of securities included in each centrality-sorted portfolio, we measure the mean standard deviation of historic returns of individual securities included in portfolio P_i at year t along with the mean market capitalisation of individual securities, mean turnover, mean book to market ratio, mean market beta and the percentage ratio of high cap companies in each portfolio. These quantities are then averaged over the period of 38 years and results are presented in Table 2. Turnover for individual stocks is calculated as the average daily traded volume over the total number of shares.

Standard deviation (Std) is a measure of risk for investments and appears to be related with the position of an asset in the financial network. Specifically, the standard deviation of daily returns for an asset i estimated for the year proceeding $(t-1)$ portfolio selection, is inversely related to the centrality of an asset in the associated financial network at year t. Over the period of 38 years, the average standard deviation of the peripheral assets is about 35% higher compared to that of central assets signifying that peripheral stocks contain a higher degree of volatility.

The average capitalization and the average percentage of high cap assets included in each portfolio lead to the conclusion that size is inversely related to the centrality of an asset, with assets of large size being more central. However, the high cap ratio provides a deeper understanding regarding the distribution of high cap assets among portfolios. We observe that while numerous low-cap assets are included in central portfolios, the number of high-cap assets included in less central portfolios is significantly smaller.

Even though the existence of the liquidity factor is not unanimously accepted in literature, Brogaard et al. (2017) relates liquidity with the default risk or otherwise known as bankruptcy risk where increased levels of liquidity are associated with lower default probabilities. The turnover of an asset, which is defined as the ratio of the daily traded volume over the total number of issued shares of a security, is a measure of liquidity according to Datar et al. (1998). For every security individually we calculate the average daily turnover for the year proceeding portfolio selection $(t - 1)$ and then we calculate the mean turnover of securities included in each centrality-sorted portfolio. Central assets (P1) are almost twice more liquid compared to the peripheral assets (P10).

The average market beta coefficient of individual securities indicates that peripheral assets have a considerably lower sensitivity to market risk in contrast to the central assets which display a strong relation to the market risk. The same phenomenon has been reported by Eom et al. (2006); Peralta and Zareei (2016), even though both papers use a different approach for constructing the financial networks. The question is though, do central asset have high sensitivity to the market risk or market is highly depended on the performance of the central assets.

Table 2 reveals the close relationship between capitalisation of an asset and its centrality with highly capitalised assets obtaining, on average, more central positions in the financial network. Taking into consideration the fact that the majority of available market indices are value-weighted with high capitalised securities contributing significantly more in the performance of an index, we can infer that in fact market indices have high exposure to central assets and not the opposite. That makes central securities systematically important and vital for the stability of the market and peripheral assets are not affecting the performance of the overall market as much as central assets do.

Even though the book to market ratio does not exhibit a strong monotonic relationship with centrality, the ratio remains low for the central portfolio (P1) and is considerably larger for the three most peripheral portfolios (P8, P9, P10). This implies that central assets are overvalued and peripheral assets are undervalued given their intrinsic value.

Comparing Table 1 and Table 2, we observe that the peripheral portfolio (P10) has the minimum standard deviation on its realised returns while including the most volatile assets. This phenomenon seems rather odd, if we do not consider the effect of diversification. In this direction, we use a quantitative formula which measures the degree of diversification for each portfolio aiming to explain the aforementioned observation.

The diversification formula is based upon the hypothesis that a perfectly correlated portfolio, i.e. in case where for every pair of assets i and j in a portfolio correlation $\rho_{i,j} = 1$, the diversification the formula defined as:

$$div_p = \frac{w_1\sigma_1 + w_2\sigma_2 + ... + w_n\sigma_n}{\sigma_p}, \tag{7}$$

should equal $div_p = 1$. This is the lower boundary of the formula. The coefficient $w_i \in [0, 1]$ is the ratio of capital invested in asset i and $\sum_i w_i = 1$. The n defines the number of assets included in a portfolio and σ_p is the standard deviation of the realised returns of a portfolio.

According to Markowitz (1952), in diversified portfolios, the standard deviation of returns is less than the weighted average of standard deviations of returns of individual assets. Idiosyncratic risk among assets cancels out and the minimum attainable volatility of a portfolio is its exposure to systematic risk. This implies that the higher the degree of diversification in a portfolio, the lower the standard deviation of the portfolio is which in fact results higher scores for the diversification index.

Table 2 reports the diversification score for each portfolio. The value of the diversification index increases monotonically as less central stocks are considered signifying that more peripheral portfolios in fact benefit from the effect of diversification that leads to reduced risk exposure. This fact validates our previous assertion that central assets display a ”herding” behaviour meaning that the price of central assets tend to move in the same direction and no diversification can be achieved by investing only on those central assets. Contrary to that, peripheral assets display an ”unique”, ”independent” or even ”contrarian” behaviour compared to the rest of the market. The diversification index increases for more peripheral portfolios fact, that leads the idiosyncratic risk of stocks to cancel out leading to less volatility in the portfolio. The diversification index provides a reasonable explanation of why other scientists (Onnela et al. (2002); Peralta and Zareei (2016); Baitinger and Papenbrock (2016)) have reported that peripheral assets are those being allocated non-zero weights in the Markowitz minimum variance portfolio.

In the next sub-section, we model cross-sectional return variation for the centrality-sorted portfolios aiming to capture the risk exposure of these portfolios and to provide evidence that the interconnectedness risk factor is priced in US equities markets. This analysis is expected to shed some light on the risks factor that compensate investor for undertaking an investment in the peripheral assets.

6.2 Risk factor analysis

CAPM is one of the earliest asset pricing models presented in financial literature (eq. 8), yet it still remains the cornerstone for numerous models which have been developed mainly by extending or augmenting the single factor market model with more factors that capture cross-sectional return variation. The three factor (eq. 9), and more recently the five factor model (eq. 10), introduced by Fama and French (1993, 2015), the Carhart (1997) four factor model which extends the three Fama-French with the momentum factor (eq. 11), the four factor model proposed by Pástor and Stambaugh (2003) that expands the three factor Fama-French model with liquidity (eq. 12) are some of the most well-studied asset pricing models presented in literature for capturing exposure of portfolios and individual securities to common risk factors. In the context of our research, we estimate the following models for the centrality-sorted portfolios using the Ordinary Least Square (OLS) regression for estimating the coefficients of the independent variables for the following models:

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + \epsilon_{p,t} \tag{8}$$

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + b_s smb_t + b_v hml_t + \epsilon_{p,t} \tag{9}$$

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + b_s smb_t + b_v hml_t + b_{pr} rmw_t + b_i cma_t + \epsilon_{p,t} \tag{10}$$

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + b_s smb_t + b_v hml_t + b_{mo} umd_t + \epsilon_{p,t} \tag{11}$$

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + b_s smb_t + b_v hml_t + b_{lq} iml_t + \epsilon_{p,t} \tag{12}$$

$$r_{p,t} - r_{rf,t} = \alpha_p + b_m mk_t + b_c pmc_t + \epsilon_{p,t} \tag{13}$$

where $r_{p,t}$ refers to monthly returns of centrality-sorted portfolio p at time t, $r_{rf,t}$ is the risk free rate, mk_t is the market excess return $r_{m,t} - r_{rf,t}$, smb_t is the portfolio mimicking the size factor, hml_t is the value factor portfolio, rmw_t is the operational profitability factor, cma_t is the investment style factor, umd_t is the portfolio capturing the momentum factor, iml_t is the Pastor-Stambaugh traded liquidity factor and pmc_t is the interconnectedness risk factor portfolio introduced in this work.

Before presenting the output of the aforementioned regression models, we present some statistics for the factor portfolios. In Table 3, Panel A, we present the mean monthly return ($\bar{r_p}$), the standard deviation ($\sigma(r_p)$) and the risk-adjusted returns ($\bar{r_p}/\sigma(r_p)$) of the corresponding factor portfolios. The mean returns indicate the reward that investors receive by perfectly aligning their investment portfolio with the corresponding risk factor and risk adjusted returns show the reward per unit of risk that each risk factor offers as compensation to investors.

The size portfolio (smb) offers the least average monthly returns and the interconnectedness factor portfolio (pmc) has the highest performance measured both by mean returns and risk-adjusted returns. Investors are compensated with a higher risk premium when undertaking investments with positive exposure to the interconnectedness risk factor compared to any other common risk factor included in the analysis.

Previously, we show that the standard deviation of daily historic returns, liquidity, market capitalisation, exposure to market risk and the book to market ratio of an asset are related to its position in the financial network. In order to provide evidence that the interconnectedness risk factor portfolio pmc does not act as a proxy of other known factors but rather it is a stand alone risk factor, in Table 3, Panel B, we append the correlation matrix of the risk factor portfolios. The pcm portfolio displays low correlation with the majority of risk factors included in our analysis. In absolute terms, the market portfolio has the largest correlation with the pmc factor, which is expected given that both factors capture different aspects of systematic risk. Strong correlation is also observed with the momentum portfolio and this relationship is inherited by the correlation structure preserved when constructing the network.

What is not expected though, is the moderate positive correlation with the investment style factor portfolio i.e. conservative-minus-aggressive. This indicates, partially, that peripheral equities are characterised as conservative, while the central are more aggressive. Even though, we cannot derive a rule purely based on correlation, that is an indication.

The rest of this subsection is dedicated on explaining the source of cross-sectional return variability of the centrality-sorted portfolios.

Table 4 reports the estimated parameters of the CAPM model (eq. 8) when monthly returns of the centrality-sorted portfolios are used as dependent variables. Numbers in parenthesis report the t-statistics. The single factor market model appears to perform well on explaining cross-sectional variation of returns for the central portfolio, P1, with $R^2 = 0.82$. However, it does not perform equally well on explaining cross-sectional variation of less central portfolios with $R^2 = 0.59$ for the most peripheral portfolio P10.

The estimated slope of the market factor $\hat{\beta}_p$ decreases monotonically as more peripheral assets are included in a portfolio indicating the lessened exposure of peripheral assets to market risk. The explanatory power of the model also decreases monotonically and we should point out the poor fitting of the CAPM model on the pmc portfolio (10-1), where $R^2 = 0.3$. The estimated constant $\hat{\alpha_p}$, known as the active return, indicates to which extent returns achieved by portfolio p remain unexplained given the exposure to risk factors. Under the CAPM, the active return of Portfolio1 equals zero, statistically speaking. However, as less central assets are included in a portfolio, active return also increases and Portfolio10 has about 12% annualised active returns.

The pmc portfolio delivers a risk adjusted return of 0.96% per month with t-statistics being equal to 6.23 and it has an active beta since peripheral portfolio P10 has a much lower market beta compared to central portfolio P1.

The fact that the CAPM model can only explain a small portion of the cross-sectional return variation for the pmc portfolio indicates that the risk premium awarded to investors with a positive exposure to the interconnectedness risk factor is not solely related to exposure to the market factor directly. Even though Ahern (2013) asserts that the peripheral-minus-central portfolio constructed based on industrial networks could potentially act as a proxy for the market factor, our results show that the market factor portfolio and the pmc portfolio capture opposite directions in return variation.

Enhancing the original CAPM model with the size and value factor, eq. 9, we model cross-sectional return variation using the three-factor model as suggested Fama and French (1993). Table 5 reports the estimated model for each portfolio. Compared to the CAPM model, the addition of the factors adds explanatory power to the model given that R^2_{abj} is improved for the majority of the models presented. Furthermore, active returns $\hat{\alpha}_i$ are decreased indicating the size and value factors are indeed priced in the centrality-sorted portfolios.

Noteworthy is the fact that the coefficients of the size portfolio (β_{smb}) are significantly higher than those of the value portfolio indicating that the centrality-sorted portfolios hold a higher exposure to the size factor. Table 2 shows that there is a negative monotonic relationship between the size and centrality of a security while the relationship between the book to market ration and centrality is not so strong, which explains a weaker exposure to the corresponding risk factor portfolio.

Furthermore, the central portfolio (P1) containing the largest securities measured by capitalisation is expected to have a negative exposure to the size factor portfolio (smb), yet we observe that the coefficient $\beta_{smb,p1}$ is positive. This phenomenon is explained by the fact that even the central portfolio (P1) contains assets the majority of which are low capitalization assets (Table 2). High cap assets compose only 46% of the portfolio and the other 54% consists of small cap assets.

Adding the size and value factors into the CAPM model we notice that the alpha spread becomes slightly reduced for 0.96 to 0.91 for the 10-1 portfolio (pmc). The explanatory power of the size factor (smb) is significant on the pmc portfolio which is expected because the P10 consists of small cap stocks. Results suggest that the size and interconnectedness factors are related but capture different sources of variance in stock markets.

Table 3 illustrates that the momentum factor portfolio (umd) has the highest positive correlation with the pmc portfolio and thus, the Carhart (1997) four factor model (eq. 11) including the momentum factor is considered. The explanatory power of the model, measured by the R^2, is improved for the central portfolios compared to the three factor Fama-French model, yet for peripheral portfolios there is not considerable improvement. As expected, P10 does not appear to receive any premium related to momentum factor. In section 3, we presented the economic intuition of the network approach asserting that peripheral assets do not follow the prevailing trends but rather display "unique" patterns in the return series. The statistically insignificant coefficient on the momentum factor validates our intuition. P1 appears to be highly influenced by the momentum factor negatively indicating that central securities tend to be low momentum assets.

Given that the peripheral portfolio has almost zero exposure to momentum factor since P10 contains the least correlated assets in the stock market and the central portfolio P1 contains the most correlated ones, the portfolios P10-P1 has a positive exposure to the momentum factor. Overall, the momentum factor (umd) seems to absorb 1/3 of the abnormal returns of the pmc portfolio, because we sort the most active momentum stocks and long the least momentum stocks.

The fact that the four-factor model including the market, size, value, momentum can explain a significantly smaller portion of the cross-sectional variation of returns of the peripheral portfolios P10, leads to investigate which other factors could possibly add some insight into the risk premium received by peripheral assets.

The four factor model including the liquidity factor proposed by Pástor and Stambaugh (2003) is considered and results are presented in Table 7. As observed, the majority of the centrality-sorted portfolios do not receive any liquidity premium and the magnitude of the coefficient is significantly low in cases where the coefficient is indeed significant showing that the liquidity factor is not priced in the centrality-sorted portfolios. In fact, this phenomenon does not come as a surprise taking into consideration that the turnover is only weakly related to centrality. In Table 2 only portfolio P8, P9 and P10 show a considerably lower degree of liquidity compared to the other portfolios considered.

Then, the five factor model proposed by Fama and French (2015) is considered including the market factor, size, value, investment style and operational profitability factor (eq 10). Results are presented in Table 8. The investment style and operational profitability factor do not appear to be priced factors for the majority of centrality-sorted portfolios and the corresponding coefficients are statistically insignificant. Centrality-sorted portfolios hold no exposure to the investment style and operational profitability factor. The only exception is portfolio P1 that has a negative and statistically significant loading into the investment style factor. This phenomenon validates our previous assumption that central assets are considered as the aggressive assets, following the definition of aggressive as provided by Fama and French Fama and French (2015).

The main outcome of this analysis is the relationship that connects higher earnings on stock returns with centrality. The superior returns of peripheral portfolios remain unexplained even after controlling for common risk factors concluding that common asset pricing models do not explain the cross-sectional return variation in centrality-sorted portfolios. Centrality-sorted portfolios do not present a uniform loading on the presented risk factors recommending that risks factors in fact capture part of cross-sectional return variation yet, there is a part of the return variation which can only be explained by the exposure to interconnectedness risk.

In Table 9 we present the coefficients and the R^2 for the model in eq. (13), which is a 2-factor model augmenting the CAPM model with the interconnectedness factor (pmc). Since we argue that they both serve as factors capturing two different aspects of systematic risk or market risk, we show their joint effect on capturing cross-sectional return variation of the centrality-sorted portfolios.

The first thing to notice is that the coefficient $\hat{\alpha}_p$ becomes insignificant in the presence of the pmc factor for the majority of centrality-sorted portfolios, with an exception for P1 and P10. The positive $\hat{\alpha}_p$ coefficient could be attributed to the negative correlation between the independent variables. Not to mention that both P1 and P10 are constituents of the pmc portfolio. It is also worth mentioning that P1 and P2 have a negative loading to the pmc factor, P3 shows no exposure while all other portfolio display an incremental exposure to the pmc factor. Even though the performance of the model as measured by R^2_{adj} increases for all portfolios, the 2-factor model vanishes the active alpha.

We argue that the interconnectedness risk supplements the market factor in capturing systematic risk. Assuming that the pcm portfolio acts as a proxy for the market portfolio then we would expect that both portfolios capture the same degree of variation of cross-sectional returns, yet in Table 4 the reported $R^2 = 0.3$ when the CAPM model is applied on the pmc portfolio. This proposes a low explanatory power of the single factor market model on the variation of returns of the pcm portfolio. In addition, the sign of the β_{pmc} is negative indicating that returns of the two portfolio are moving towards opposite directions.

To further support our argument, in Table 10 we present results of the model in eq. 11 where the market mimicking portfolio has been replaced by the pmc factor portfolio. We observe that the performance of the model, measured by the R^2 is inferior compared to the original four factor model and that the active return (alpha) remains high. Given the negative relation between the market and the pmc portfolio, it is no surprise that portfolios have a negative exposure to the pmc portfolios, but it is surprising the fact that in the presence of the pmc portfolio the value proxy portfolio (hml) becomes statistically insignificant.

In the absence of the market portfolio, the pmc factor acts as a proxy for market risk since it is the only portfolio capturing part of the systematic risk, yet its contribution on capturing cross-section return variation of the individual portfolios is not as strong as the market portfolio itself. However, when the market portfolio is used as a standalone risk factor capturing systematic risk (see Table 11) the model fails to adequately explain return variation for the less central portfolios. Results on Table 10 indicate that market and pmc factor acts as supplementary factors capturing different aspects of systematic risk.

6.3 Testing validity of pmc factor over time

The prevailing circumstances in financial markets change frequently and an important question is whether the performance of a model is consistent over time and whether the risk factors have a persistent impact on explaining cross-sectional return variation of securities. It is commonly believed that financial markets are not static but rather they evolve over time. Changes in legislation and operation rules, changes in the infrastructures and technology as well as changes to market conditions could lead to radical changes to the way that trading is conducted.

A profound technological improvement that affected the structure of stock market was the introduction of algorithmic and high frequency trading which became particularly popular with the new millennium. This implies that trading securities today probably is not the same as 40 years ago. Similar structural changes and especially changes in market conditions might affect the accuracy of pricing models.

To this end, we examine if the factor-loading of the centrality-sorted portfolios remain consistent through time. More specifically, we estimate the Carhart (1997) four factor model as in eq. 11 for all centrality-sorted portfolios. The proposed methodology dictates to split the return series of the centrality-sorted portfolios into two different periods separating the original 38 year period into two sub-periods of equal size and to independently fit the pricing model in eq. 11. Table 11 presents the coefficients along with their corresponding t-stats and the R^2 for two sub-periods, i.e. period $02/01/1981 - 31/12/1999$ and $03/01/2000 - 31/12/2018$.

It is important to acknowledge that the second period could be characterized as more turbulent. Both the Dot.com bubble and the Subprime mortgage crisis, who originated in US, along with the Chinese stock market crisis in 2015 and the energy crisis of 2016 are included in the second period of study. The first period contains only the Black Monday (1987) whose duration was short.

In Table 11 one can observe the decrease in the performance of the model during the second period, especially for the peripheral assets. The most noticeable change is that of the value portfolio (hml) for P1. In the first period the P1 portfolio shows a negative exposure to the value factor while this dependency vanishes in the second period. Moreover, in the first period the alpha is considerably higher compared to the second period for the majority of the portfolios. Despite the small number of differences being identified between the two periods, we can argue that the phenomenon of peripheral assets outperforming central ones remains stable during both periods. The performance of the model measured by R^2 does not show large deviations over time.

In Table 12 we expand the Carhart (1997) four factor model with the pmc factor. In the presence of the pmc factor, one can notice that the explanatory power of the model, measured by the R^2, remains stable between the two periods. We also observe that the coefficients of the pmc factor remain statistically significant over time yet, in the second period it is portfolio P4 that displays no exposure to the pmc portfolios compared to the first period where the P3 portfolio has this attribute. This can be explained by the fact that the number of assets traded in the stock market increased in more recent years and the temporal structure of the network changes. Generally speaking, the exposure of the assets to the interconnectedness risk does not appear as a temporal feature but rather there is a deeper relationship that connects expected returns with the Centrality Index of an asset.

Rather questionable is the fact that coefficients of the value factor portfolio hml present different patterns between the two periods. In the first period only 4 out of 10 coefficients are statistically significant while in the second period all coefficients are significant. In addition, over the first period the constant α_p is not significant for most portfolios fact which is not true for the second period. Even though this phenomenon requires deeper analysis, our interpretation is that changes of infrastructures in the financial markets and changes in the market conditions have created opportunities for traders that lead to superior active returns.

6.3.1 Interconnectedness risk and 25 size/value F-F portfolios

In this section we perform an out-of-sample robustness test for the proposed interconnectedness risk factor aiming to reveal its importance by eliminating any bias and testing its explanatory power on portfolios that are not centrality-sorted. Given the low correlation between the interconnectedness factor with the size and the value factors as reported on Table 3, the 25 double-sorted portfolios on size and value proposed by Fama and French (1993) are used as a benchmark.

As originally stated by Lewellen et al. (2010) and Daniel et al. (2012) and also rephrased by Ahern (2013), the aforementioned portfolios have an inherent factor structure and the use of other factors as explanatory variables might fail to capture cross-sectional variation in other, unspecified dimensions of variation. In other words, these portfolios have been created holding exposure to specific factors and thus, including factors not being considered throughout the formation process might lead to rejecting the importance of other factors. Consequently, failing to identify the statistical significance of the pmc factor on the 25 size/value portfolios does not diminish its importance, yet concluding statistical significance in these portfolios increases the robustness of the factor.

In Table 13, we present the coefficients of the regression model:

$$r_p - r_{rf} = \hat{\alpha}_p + b_{p,m} * mk_t + b_{p,smb} * sbm_t + b_{p,hml} * hml_t + b_{p,pmc} * pmc_t + \epsilon_p. \tag{14}$$

when applied to the aforementioned 25 portfolios.

Since these portfolios have been created with an inherent exposure to value and size factors, we model the cross-sectional returns of these portfolios using the three factor Fama-French model augmented with the pmc factor and results are presented in Table 13.

The variables s and b in the first column signify the rank of the size and value of assets being included in each portfolio correspondingly. Size is the first dimension of the double-sorted portfolios and value is the second dimension. Thus, $s1$ refers to the group of stock including the smallest among the assets and $b1$ refers to the group of stock including the assets with lowest book-to-market ratio within the $s1$ group.

We observe that the pmc factor is a statistically significant factor when explaining the cross-sectional variation of the returns of the presented portfolios for 18 out of 25 cases. In some cases only, the magnitude of the exposure of some portfolios to the pmc factor measured by the absolute value of the coefficient of the factor is comparable with that of other well known factors such that the value factor. For instance, for portfolio $s1b1$ the $|\hat{\beta}_{s1b1,hml}| = 0.24$ while the $|\hat{\beta}_{s1b1,pmc}| = 0.20$. This indicates that the exposure of portfolio $s1b1$ to the interconnectedness factor is similar to that of the value factor.

It is important to note that there is a relation between size of assets being included in each size-value double-sorted portfolio and its exposure to the pmc factor. Every portfolio included in the $s1$ size group has a positive exposure to the interconnectedness risk factor while the remaining size groups have a negative exposure to pmc factor. One might observe that the magnitude of the exposure to the proposed factor decreases as we move from group $s2$ towards $s5$. In the $s5$

almost all coefficients are statistically insignificant indicating that the group of largest assets does not hold a considerable exposure to the pmc factor, yet the factor is important for the small size assets. Similar evidence has been provided in previous sections as well.

The fact that the pmc factor contributes in a statistically significant way on explaining variation of returns of portfolios which are not formed taking into account the centrality of assets gives an indication that the pmc factor is a universal risk factor which compensates investors with higher returns when exposure to this factor is undertaken.

To further illustrate the validity of the interconnectedness risk factor, in Table 14, we report the findings of the model in eq. 14 in the 12 industrial portfolios constructed by Fama and French. Even though these portfolio are selected purely based on the operating industry of the companies included in the sample, the pmc factor appears to have a significant contribution on explaining cross-sectional return variation of these portfolios in 7 out of 12 cases.

However, previous work from Ahern (2013) indicated that individual industries hold their own position in the network and Mantegna (1999) showed the central role of financial companies in the associated financial network. Under these circumstances, it is no surprising that the Money sector has no exposure to the pmc factor. The central role of its constituents in the financial network removes the effect of the pmc factor. Sectors where its constituents play a less central role in the associated financial networks show a statistical significant loading to the pmc factor.

6.4 Bet-Against-the-Beta factor and the Interconnectedness risk

Frazzini and Pedersen (2014) introduce the betting-against-beta (bab) factor portfolio which consists of a long position on low beta securities and a short position on high beta securities. In the aforementioned paper, the proposed bab factor portfolio is found to consistently outperform the corresponding factor mimicking portfolios of common risk factors such as value, momentum etc in terms of Sharpe ratio. Modelling the variation of cross-sectional returns of the bab portfolio using numerous models including the CAPM model, three factor and five factor Fama-French models, they found that no model is able to adequately capture variation of cross-sectional returns and the coefficient $\hat{\alpha}$ measuring active returns remains positive and statistically significant.

Table 2 shows the relationship that links the position of a security in the associated financial network and its exposure to market risk. Findings indicate that assets with low Centrality Index have a low market beta β_m coefficient in the CAPM model. In this section we provide evidence that the pmc factor portfolios captures a significant portion of cross-sectional return variation for the bab factor portfolio indicating that the interconnectedness risk factor is priced risk factor for the bab factor portfolio.

In the rest of this section we present various pricing models used as a vehicle to explain the cross-section return variation of the bab factor portfolio.

Each column on the Table 15 represents a different model and analysis includes the following models: the CAPM model denoted by *CAPM*, a single factor model including the Interconnectedness risk portfolio denoted by *pmc*, a two factor model including the market and interconnecteness risk factors, *CAPM+pmc*, the three factor model by Fama and French (1993) denoted by *3F*, the three factor model augmented with the pmc portfolio, *3F+pmc*, the five factor model by Fama and French (2015) denoted by *5F* and the five factor model augmented with the pmc portfolio (*5F+pmc*), the five factor model with momentum and liquidity denoted by *5F+imp+umd* and finally the five factor with liquidity, momentum and interconnectedness (*5F+iml+umd+pmc*).

Our purpose is to illustrate that the pmc factor captures a large portion of cross-sectional return variations of the bab factor portfolio and that the addition of pmc factor improves the performance of well known models when modelling cross sectional returns of the bab portfolio. Including the pmc factor portfolio in the independent variables of the pricing models increases significantly the performance of the models as reported in Table 15.

We observe that even though the bab factor portfolio is constructed with regards to the market beta coefficient, the CAPM model has little effect on capturing cross-sectional return variation of the bab portfolio. The $R^2 = 0.037$ and the active returns are close to 12.7% annualised returns. In contrast, when the pmc factor is used as a standalone factor captures a significant higher degree of variation in returns ($R^2 = 0.29$). The addition of the pmc portfolio in the original CAPM model shows the join effect of these factors which supplement each other on capturing systematic risk.

Active returns α_i is about 6.4%, almost half of the CAPM model standalone and also lower than the single factor pmc model.

Starting with the simple market factor model (CAPM), we observe that the addition of risk factors such as size, value, operational profitability, investment style, momentum and liquidity, consistently improves the performance of the model. It is apparent, though, that including the pmc factor portfolio in the model has a direct impact in the performance of the model.

Augmenting the $3F$ model with the pmc factor portfolio, results show that the $3F + pmc$ model explains three times more variance in the returns of the bab model and annualised active returns drop from 11.4% to 3.6% which becomes statistically insignificant. Similar results are presented when the $5F$ model is considered. Even though the $5F$ model performs significantly better compared to the $3F$ model, the addition of the pmc factor makes active returns equal to zero indicating that bab portfolio compensates investors only for their exposure to risk factor including the interconnectedness risk factor.

The contribution of the pmc factor portfolio on explaining cross-sectional return variance of the bab portfolio is apparent. The question now is, to which extent the bab portfolio contributes on explaining cross-sectional return variation of the interneccentectedness risk factor portfolio *pmc*. In Table 16 we present the models that we included in Table 15, with the only difference that pmc portfolio is now the dependent variable and the bab portfolio replaces the pmc portfolio as independent variable.

The bab factor appears to be a priced risk factor for the pmc portfolio taking into consideration that active returns are zero when bab is used as a standalone factor. However, when bab is used as standalone factor the performance of the model is poor, since the model explains only a small portion of return variation. In fact, even the CAPM model has marginally better fit on the returns of the pmc portfolio.

The combined effect of bab and the market factors leads to annualised active returns of approximately 5% while the $R^2_{adj} = 0.5$. In the three Fama and French model, the pmc portfolio holds a positive and statistical significant load on the size portfolio contrary to the bab portfolio which holds a positive load on the value factor. This phenomenon indicates that the two factor portfolios are awarded with risk premium related to different risk factors. This could serve as an indicator that the two factor portfolios do not act as a proxy of one another even though they appear to have a strong relationship.

When the five Fama and French model ($5F$) is estimated for the returns of pmc portfolio, only the market and the size factor appear to be statistically significant, while when the model is extended with the bab factor, due to correlation between the independent variables, only the investment factor is not contributing in the overall performance of the model. In the five factor model augmented with liquidity and momentum, only the market factor along with the size and momentum factor are statistically significant.

The model including the five factor model augmented with liquidity, momentum and the betting-against-beta is the model displaying the best fit on explaining cross-sectional return variation for the pmc portfolios. In this model the value factor, the investment factor as well as the liquidity factor are not contributing in explaining cross-sectional return variation and consequently, investors get compensated for their exposure to market risk, size risk, operational profitability risk, momentum risk and betting-against-beta risk. Even though a broad range of risk factors is considered, active returns remain positive and statistically significant providing strong evidence that there is part of return variation explained only by the exposure to the interconnectedness risk.

7 Conclusion

The focus of present work is to provide evidence that the Interconnectedness risk factor, which is related with the interdependence among securities is indeed a priced risk factor in the USA financial markets and that investors are awarded with higher returns when undertaking a positive exposure to this factor,

Creating 10 centrality-sorted portfolios, our findings suggest that the position of an asset in the associated financial network is related to its expected performance and to its exposure to market risk measured by market beta (β_m). Portfolios including peripheral securities outperform those including central ones, and risk-adjusted returns display a monotonically increasing trend as less central assets are included in a portfolio.

We use common risk factors as independent variables in various models aiming to capture variation of cross-sectional returns of the centrality-sorted. Exposure to factors such as the market risk, size, value and momentum risk factor appear to be priced for the centrality-sorted portfolios, while the portfolios do not display exposure to factors such as liquidity, operational profitability and investment style factor.

The interconnectedness risk factor portfolio (pmc) consists of a long position on the portfolio containing the peripheral assets and a short position on the portfolio containing the central assets. We show that pmc factor portfolio has a statistically significant contribution when modelling cross-sectional returns variation of the centrality-sorted portfolios yet, this factor appear to be priced even in out-of-sample portfolios such as the 25 size-value double sorted portfolios as well as the 12 industrial portfolios proposed by Fama and French.

We argue that the proposed interconnectedness risk factor captures the systematic importance of an asset and acts as a supplement to the market risk when measuring the systematic risk exposure of an security.

At last, we show the interconnectedness risk factor provides a sensible explanation for the well-known bet-against-the-beta (bab) price anomaly reported by Frazzini and Pedersen (2014) which up to date remains a puzzle for those involved in the study of financial markers. The interconnectedness risk factor is a priced factor for the bab factor portfolio and has a large contribution on explaining its cross-sectional returns variation.

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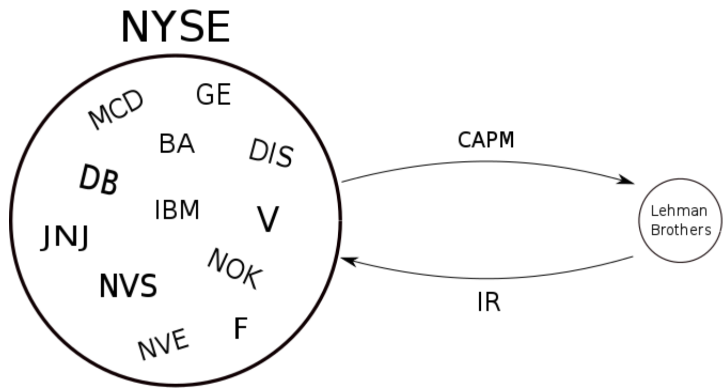

Figure 1: Explaining the relationship between Interconnectedness Risk (IR) and CAPM model. The IR model captures the influence of a stock on the performance of the market while the CAPM encaptulates the effect that the market has on specific asset.

Table 1: **Monthly performance statistics for the centrality-sorted portfolios.** Monthly performance statistics for the centrality-sorted portfolios P_i, $i \in 1, 2, .., 10$ for the period January 1981- December 2018. The realised average monthly return ($\bar{r_p}$) and the standard deviation ($\sigma(r_p)$) are calculated using raw returns while the Sharpe ratio and the t-statics use raw returns after subtracting the risk free rate. Returns and standard deviation are in percent.

Portfolio	$\bar{\mathbf{r_p}}$	$\sigma(\mathbf{r_p})$	**Sharpe ratio**
1 (central)	1.09	5.9	0.12
2	1.09	5.6	0.13
3	1.23	5.4	0.16
4	1.24	5.3	0.17
5	1.27	5.2	0.18
6	1.32	5.1	0.19
7	1.46	4.9	0.23
8	1.45	4.8	0.23
9	1.48	4.7	0.24
10 (peripheral)	1.74	4.2	0.34
10-1	0.65	3.9	0.08

Table 2: **Profiling assets included in the centrality-sorted portfolio**

Quantitative profile for assets included in the centrality-sorted portfolio P_i, $i \in 1, 2, .., 10$. The first column indicates the corresponding portfolio, second column reports the average standard deviation (Std) of daily returns of assets being included in each portfolio for the year prior to portfolio selection. The third column measures the average capitalization (market cap) of assets included in a portfolio at the day of portfolio selection and the fourth column the average liquidity (turnover) measured by the average daily volume to total shares ratio over the year prior to portfolio selection. *Market beta* is the average value of market coefficient β_i for assets in every portfolio when the CAPM model is fit on daily returns of the year proceeding portfolio formation. *Boot to market ratio* is the average value of the ratio calculated at the day of portfolio selection for assets included in each portfolio. The column *high cap ratio* measures the ratio of high capitalisation assets (as defined by Fama and French Fama and French (1993)) included in each portfolio over the total number of assets. High cap ratio represents the percentage of stocks which belongs to the top 1/3 largest stocks. The aforementioned measures are averaged over the period of 38 years under study. Standard deviation, turnover and high cap ration are reported in percent. The Diversification score (div score) calculated as indicated in eq. 7 quantifies the degree of diversification of assets being included in a portfolio. The table below shows the Diversification index for every portfolio P_i, $i \in 1, 2, .., 10$ calculated using monthly returns for the period January 1981 - December 2018. A higher diversification score indicates a higher degree of diversification within the portfolio.

Portfolio	**Std**	**market cap**	**turnover**	**market beta**	**book to market ratio**	**high cap ratio**	**div score**
1 (central)	2.6	7.457 bn	0.65	0.94	0.56	46	2.33
2	2.8	4.205 bn	0.66	0.80	0.62	30	3.03
3	2.9	3.550 bn	0.64	0.73	0.70	25	3.33
4	3.0	2.731 bn	0.62	0.67	0.65	19	3.65
5	3.1	2.365 bn	0.62	0.61	0.67	16	3.99
6	3.2	1.935 bn	0.59	0.56	0.69	13	4.37
7	3.3	1.659 bn	0.56	0.50	0.71	11	4.69
8	3.3	1.372 bn	0.51	0.44	0.81	09	5.08
9	3.4	0.888 bn	0.47	0.37	0.76	05	5.95
10 (peripheral)	3.5	0.250 bn	0.30	0.21	0.87	01	6.94

Table 3: **Descriptive Statistics and Correlations for factor portfolios**
Panel A: Monthly performance statistics for the factor portfolios. The first row indicates the average realised (raw) monthly return, the second row contains the average monthly standard deviation and the third raw the risk-adjusted returns. Columns correspond to the factor portfolios.
Panel B: Correlation matrix of monthly returns of the factor portfolios. Each value corresponds to the Pearson correlation ($\rho_{i,j}$) between the return series of each pair of factors.
The market portfolio is indicated as mk, the size portfolio as smb (Fama and French (1993)), the value portfolio as hml (Fama and French (1993)), the operetional profitability as rmw (Fama and French (2015)) , the investment style as cma (Fama and French (2015)), the momentum portfolio as umd (Carhart (1997)), the liquidity portfolio as iml (Pástor and Stambaugh (2003)) and the interconnectedness factor as pmc. Monthly data for the market, size, value, operational profitability and investment style factor are obtained by the Kenneth French's website. Data for momentum factor portfolio are obtained from the CRSP database and data for the traded liquidity factor are obtained from Pastor L. (2019).
Analysis covers the period January 1981 - December 2018. Raw returns and standard deviation are in percent.

Panel A: Performance Statistics

	mk	smb	hml	rmw	cma	umd	iml	pmc
$\bar{r_p}$	0.61	0.08	0.31	0.35	0.30	0.53	0.44	0.65
$\sigma(r_p)$	4.36	3.00	2.90	2.37	1.99	4.38	3.48	3.88
$\bar{r_p}/\sigma(r_p)$	0.14	0.03	0.11	0.15	0.15	0.12	0.12	0.17

Panel B: Correlations

	mk	smb	hml	rmw	cma	umd	iml	pmc
mk	1.00	0.21	-0.27	-0.33	-0.39	-0.17	0.01	-0.55
smb		1.00	-0.27	-0.50	-0.15	0.06	0.01	0.07
hml			1.00	0.26	0.68	-0.20	0.04	0.18
rmw				1.00	0.15	0.10	-0.06	0.12
cma					1.00	0.00	0.02	0.31
umd						1.00	0.03	0.40
iml							1.00	0.05
pmc								1.00

Table 4: **Estimating the CAPM model for the centrality-sorted portfolios.**
Parameters of the CAPM model (eq. 8) estimated for centrality-sorted portfolios on monthly returns after subtracting the risk-free rate. For the Portfolio 10-1 the raw returns are used. The market portfolio is indicated as mk and monthly data for the market mimicking portfolios are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{\alpha}_p$	$\hat{\beta}_{mk}$	R^2_{adj}	$\rho(r_p, r_m)$
1 (central)	-0.00 (-0.02)	1.23 (45.67)	0.82	0.91
2	0.04 (0.34)	1.17 (46.25)	0.82	0.91
3	0.22 (1.93)	1.11 (43.80)	0.81	0.90
4	0.24 (2.12)	1.08 (42.52)	0.80	0.89
5	0.29 (2.48)	1.05 (39.50)	0.77	0.88
6	0.37 (3.03)	1.00 (35.93)	0.74	0.86
7	0.53 (4.43)	0.96 (34.92)	0.73	0.85
8	0.54 (4.38)	0.93 (32.84)	0.70	0.84
9	0.60 (4.80)	0.89 (31.44)	0.68	0.83
10 (peripheral)	0.95 (7.48)	0.74 (25.45)	0.59	0.78
10-1	0.96 (6.23)	-0.49 (-14.07)	0.30	-0.55

Table 5: **Estimating the 3-Factor Fama-French model for centrality-sorted portfolios.** Parameters of the 3 Factor (Fama and French (1993)) model (eq. 9) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml. Monthly data for the market, size and value factor portfolios are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	R^2_{adj}
1 (central)	-0.05 (-0.50)	1.20 (46.21)	0.34 (9.03)	0.13 (3.26)	0.85
2	-0.05 (-0.68)	1.12 (60.23)	0.58 (21.26)	0.23 (8.00)	0.91
3	0.12 (1.81)	1.06 (65.92)	0.66 (28.09)	0.23 (9.44)	0.93
4	0.13 (2.16)	1.03 (72.58)	0.70 (33.69)	0.27 (12.39)	0.94
5	0.18 (3.01)	0.99 (71.29)	0.74 (36.69)	0.28 (13.23)	0.94
6	0.26 (3.88)	0.94 (60.56)	0.76 (33.63)	0.29 (12.13)	0.93
7	0.42 (6.34)	0.90 (57.02)	0.74 (32.27)	0.28 (11.47)	0.92
8	0.44 (5.78)	0.87 (47.89)	0.72 (27.47)	0.25 (9.12)	0.89
9	0.49 (6.34)	0.83 (45.20)	0.72 (26.83)	0.26 (9.24)	0.88
10 (peripheral)	0.86 (8.89)	0.69 (30.28)	0.62 (18.71)	0.24 (6.82)	0.77
10-1	0.91 (6.06)	-0.51 (-14.40)	0.28 (5.39)	0.11 (1.99)	0.35

Table 6: **Estimating the Carhart model for the centrality-sorted portfolios.** Parameters of the 4 Factor (Carhart (1997)) model (eq. 11) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the momentum portfolio as umd. Monthly data for the market, size and value factor portfolios are obtained by the Kenneth French's website. Data for the momentum portfolio are obtained from the CRSP database.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{umd}$	R^2_{adj}
1 (central)	0.23 (2.73)	1.11 (55.10)	0.36 (12.64)	-0.01 (-0.25)	-0.36 (-18.46)	0.91
2	0.16 (2.73)	1.06 (75.49)	0.59 (29.86)	0.12 (5.85)	-0.27 (-19.92)	0.95
3	0.28 (5.08)	1.01 (75.87)	0.67 (35.46)	0.15 (7.61)	-0.20 (-15.69)	0.95
4	0.26 (4.97)	0.99 (80.27)	0.71 (40.34)	0.21 (11.0)	-0.16 (-13.47)	0.96
5	0.28 (5.06)	0.96 (73.96)	0.75 (40.74)	0.23 (11.77)	-0.12 (-9.84)	0.95
6	0.34 (5.25)	0.92 (60.14)	0.77 (35.51)	0.25 (10.7)	-0.10 (-6.82)	0.93
7	0.49 (7.41)	0.88 (55.84)	0.74 (33.44)	0.24 (10.18)	-0.08 (-5.39)	0.92
8	0.50 (6.52)	0.85 (46.37)	0.73 (28.07)	0.22 (8.03)	-0.07 (-4.05)	0.89
9	0.54 (6.85)	0.82 (43.61)	0.72 (27.17)	0.24 (8.31)	-0.06 (-3.06)	0.88
10 (peripheral)	0.90 (9.25)	0.67 (29.00)	0.62 (18.90)	0.22 (6.06)	-0.06 (-2.53)	0.77
10-1	0.67 (4.79)	-0.44 (-13.07)	0.26 (5.52)	0.22 (4.36)	0.31 (9.38)	0.45

Table 7: **Estimating the Pastor model for the centrality-sorted portfolios.**
Parameters of the 4 Factor (Pástor and Stambaugh (2003)) model (eq. 12) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the liquidity portfolio as iml. Monthly data for the market, size, value factor portfolios are obtained by the Kenneth French's website. Data for the traded liquidity factor are obtained from Pastor L. (2019). Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{iml}$	R^2_{adj}
1 (central)	-0.03 (-0.25)	1.20 (46.41)	0.34 (9.09)	0.13 (3.36)	-0.06 (-2.11)	0.85
2	-0.03 (-0.35)	1.12 (60.73)	0.58 (21.46)	0.23 (8.18)	-0.06 (-2.80)	0.91
3	0.15 (2.17)	1.06 (66.55)	0.66 (28.39)	0.23 (9.65)	-0.06 (-3.03)	0.93
4	0.15 (2.40)	1.03 (72.89)	0.70 (33.86)	0.27 (12.53)	-0.04 (-2.15)	0.94
5	0.20 (3.33)	0.99 (71.82)	0.74 (36.98)	0.28 (13.43)	-0.04 (-2.71)	0.94
6	0.26 (3.92)	0.94 (60.52)	0.76 (33.61)	0.29 (12.13)	-0.01 (-0.59)	0.93
7	0.44 (6.49)	0.90 (57.14)	0.74 (32.35)	0.28 (11.55)	-0.03 (-1.63)	0.92
8	0.45 (5.79)	0.87 (47.85)	0.72 (27.45)	0.25 (9.12)	-0.01 (-0.45)	0.89
9	0.50 (6.41)	0.83 (45.21)	0.72 (26.84)	0.26 (9.27)	-0.02 (-1.01)	0.88
10 (peripheral)	0.86 (8.86)	0.70 (30.01)	0.62 (18.90)	0.24 (6.83)	-0.01 (-0.40)	0.77
10-1	0.89 (5.87)	-0.51 (-14.43)	0.28 (5.37)	0.10 (1.93)	0.05 (1.28)	0.35

Table 8: **Estimating the 5-Factor Fama-French model for the centrality-sorted portfolios.**
Parameters of the 5 Factor (Fama and French (2015)) model (eq. 10) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the operetional profitability as rmw, the investment style as cma. Monthly data for the market, size, value, operational profitability and investment style factor are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{rmw}$	$\hat{\beta}_{cma}$	R^2_{adj}
1 (central)	0.00 (0.30)	1.17 (41.97)	0.35 (8.40)	0.23 (4.51)	-0.00 (-0.08)	-0.24 (-3.12)	0.85
2	0.04 (0.44)	1.11 (55.17)	0.60 (19.83)	0.29 (7.67)	0.04 (0.97)	-0.15 (-2.61)	0.92
3	0.14 (2.02)	1.04 (60.10)	0.65 (24.91)	0.25 (7.71)	-0.02 (-0.67)	-0.04 (-0.91)	0.93
4	0.14 (2.28)	1.03 (66.29)	0.70 (30.37)	0.29 (10.24)	0.00 (0.138)	-0.06 (-1.46)	0.95
5	0.17 (2.84)	0.99 (65.46)	0.75 (33.40)	0.29 (10.47)	0.03 (1.03)	-0.04 (-0.94)	0.94
6	0.22 (3.28)	0.95 (56.33)	0.78 (30.97)	0.27 (8.66)	0.06 (1.89)	0.02 (0.49)	0.93
7	0.39 (5.67)	0.90 (53.04)	0.76 (29.89)	0.27 (58.40)	0.07 (2.09)	0.01 (0.12)	0.92
8	0.42 (5.24)	0.87 (44.39)	0.74 (25.21)	0.24 (6.59)	0.05 (1.42)	0.01 (0.22)	0.89
9	0.44 (5.48)	0.85 (42.61)	0.75 (25.31)	0.23 (6.34)	0.10 (2.71)	0.04 (0.67)	0.88
10 (peripheral)	0.83 (8.24)	0.70 (28.03)	0.64 (17.97)	0.22 (4.79)	0.06 (1.21)	0.03 (0.38)	0.77
10-1	0.82 (5.29)	-0.47 (-12.35)	0.29 (4.99)	-0.01 (-0.20)	0.06 (0.40)	0.27 (2.53)	0.36

Table 9: **Estimating the CAPM model for the centrality-sorted portfolios.**
Parameter of the CAPM model (eq. 8) estimated for centrality-sorted portfolios on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk and monthly data for the market mimicking portfolios are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{\alpha}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{pmc}$	R^2_{adj}
1 (central)	0.43 (4.30)	1.01 (38.51)	-0.45 (-15.42)	0.88
2	0.17 (1.46)	1.10 (37.01)	-0.14 (-4.04)	0.83
3	0.21 (1.84)	1.11 (36.53)	0.00 (0.04)	0.81
4	0.14 (1.08)	1.14 (37.82)	0.12 (3.47)	0.80
5	0.09 (0.79)	1.15 (37.50)	0.21 (5.99)	0.79
6	0.09 (0.78)	1.15 (36.77)	0.29 (8.35)	0.78
7	0.21 (1.86)	1.12 (37.76)	0.34 (10.08)	0.78
8	0.18 (1.55)	1.11 (37.41)	0.38 (11.46)	0.77
9	0.20 (1.80)	1.09 (37.52)	0.42 (12.70)	0.77
10 (peripheral)	0.43 (4.30)	1.01 (38.51)	0.55 (18.67)	0.77

Table 10: **Estimating the CAPM model augmented with the interconnected factor.**
Parameters of the 4 Factor model (eq. 11) where the market factor has been replaced by the interconnectedness factor (pmc) estimated for each centrality-sorted portfolio on monthly returns. Analysis covers the period January 1981 - December 2018.Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{pmc}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{umd}$	R^2_{adj}
1 (central)	1.48 (9.10)	-1.02 (-21.57)	0.77 (13.88)	-0.05 (-0.89)	-0.20 (-4.88)	0.67
2	1.29 (7.50)	-0.78 (-15.66)	0.95 (16.18)	0.01 (0.09)	-0.20 (-4.45)	0.59
3	1.34 (7.78)	-0.67 (13.45)	1.00 (16.96)	0.01 (0.17)	-0.16 (-3.65)	0.56
4	1.27 (7.23)	-0.58 (-11.40)	1.02 (16.93)	0.03 (0.53)	-0.15 (-3.39)	0.52
5	1.24 (7.05)	-0.51 (-9.91)	1.04 (17.30)	0.04 (0.66)	-0.14 (-3.07)	0.50
6	1.24 (6.99)	-0.42 (-8.09)	1.04 (17.12)	0.04 (0.61)	-0.14 (-3.14)	0.48
7	1.34 (7.71)	-0.35 (-7.02)	1.00 (16.75)	0.03 (0.41)	-0.14 (-3.14)	0.46
8	1.30 (7.45)	-0.29 (-5.75)	0.96 (16.02)	-0.01 (-0.09)	-0.15 (-3.28)	0.43
9	1.30 (7.58)	-0.25 (-5.00)	0.94 (15.97)	0.003 (0.05)	-0.14 (-3.20)	0.42
10 (peripheral)	1.48 (9.10)	-0.02 (-0.39)	0.77 (13.88)	-0.05 (-0.89)	-0.20 (-4.89)	0.35

Table 11: **A robustness test over time for the Carhart model**
Parameters of the 4 Factor model (eq. 13) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the momentum portfolio as umd. Monthly data for the market, size and value factor portfolios are obtained by the Kenneth French's website. Data for the momentum portfolio are obtained from the CRSP database. Data are split into two different periods, January 1981 - December 1999 and January 2000 - December 2018. Models are estimated separately for each period. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{umd}$	R^2_{adj}
			01/1981 - 12/1999			
1 (central)	0.14 (1.59)	1.08 (49.42)	0.33 (10.17)	-0.14 (-3.59)	-0.24 (-8.91)	0.95
2	0.09 (1.27)	1.03 (57.16)	0.64 (23.92)	0.01 (0.22)	-0.24 (-10.51)	0.96
3	0.19 (2.73)	0.99 (58.92)	0.71 (28.51)	0.07 (2.19)	-0.16 (-7.54)	0.96
4	0.28 (4.04)	0.97 (57.14)	0.82 (32.63)	0.14 (4.62)	-0.13 (-6.31)	0.96
5	0.32 (4.28)	0.95 (52.29)	0.84 (31.27)	0.15 (4.73)	-0.15 (-6.80)	0.96
6	0.46 (5.20)	0.91 (42.24)	0.87 (27.11)	0.20 (5.38)	-0.13 (-5.03)	0.94
7	0.68 (7.67)	0.87 (40.85)	0.88 (27.74)	0.18 (4.91)	-0.09 (-3.41)	0.93
8	0.67 (6.46)	0.87 (34.73)	0.82 (21.96)	0.22 (4.91)	-0.13 (-4.11)	0.91
9	0.72 (7.01)	0.83 (33.81)	0.85 (23.05)	0.19 (4.48)	-0.10 (-3.42)	0.91
10 (peripheral)	0.93 (8.02)	0.77 (27.57)	0.82 (19.72)	0.29 (5.95)	-0.05 (-1.54)	0.86
			01/2000 - 12/2018			
1 (central)	0.28 (2.06)	1.07 (30.54)	0.41 (9.22)	0.08 (1.69)	-0.41 (-14.71)	0.90
2	0.26 (2.98)	1.05 (47.06)	0.57 (19.99)	0.20 (6.96)	-0.28 (-15.62)	0.95
3	0.39 (4.63)	1.00 (46.19)	0.64 (23.64)	0.22 (7.77)	-0.22 (-12.48)	0.95
4	0.27 (3.76)	1.00 (54.52)	0.63 (27.29)	0.25 (10.77)	-0.16 (-11.03)	0.96
5	0.30 (4.01)	0.96 (49.92)	0.68 (27.84)	0.28 (11.51)	-0.11 (-6.84)	0.96
6	0.28 (3.02)	0.93 (39.68)	0.70 (23.49)	0.28 (9.20)	-0.08 (-4.32)	0.94
7	0.36 (3.84)	0.87 (36.51)	0.66 (22.02)	0.29 (9.44)	-0.08 (-4.06)	0.93
8	0.38 (3.39)	0.83 (28.94)	0.67 (18.33)	0.24 (6.46)	- 0.05 (-2.36)	0.89
9	0.43 (3.66)	0.80 (26.77)	0.65 (17.02)	0.28 (7.17)	- 0.04 (-1.64)	0.87
10 (peripheral)	0.84 (5.67)	0.59 (15.49)	0.53 (11.01)	0.22 (4.56)	-0.07 (-2.45)	0.71

Table 12: **A robustness test over time for the pmc factor**

Parameters of the 5 Factor model (eq. 13) estimated for each centrality-sorted portfolio on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the momentum portfolio as umd, the interconnectedness factor as pmc. Monthly data for the market, size, value factors are obtained by the Kenneth French's website. Data for momentum factor portfolio are obtained from the CRSP database.

Data are split into two different periods, January 1981 - December 1999 and January 2000 - December 2018. Models are estimated separately for each period. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{umd}$	$\hat{\beta}_{pmc}$	R^2_{adj}
			01/1981 - 12/1999				
1 (central)	0.43 (5.46)	0.97 (46.48)	0.51 (16.07)	0.02 (0.58)	-0.17 (-7.45)	-0.37 (-10.43)	0.96
2	0.18 (2.30)	1.00 (48.54)	0.69 (22.13)	0.05 (1.55)	-0.22 (-9.40)	-0.11 (-3.10)	0.96
3	0.17 (2.35)	1.00 (50.92)	0.70 (23.53)	0.06 (1.72)	-0.16 (-7.39)	0.02 (0.58)	0.96
4	0.20 (2.78)	1.00 (51.69)	0.77 (26.17)	0.09 (2.90)	-0.25 (-7.05)	0.10 (3.10)	0.96
5	0.18 (2.35)	1.00 (50.58)	0.75 (24.87)	0.07 (2.17)	-0.19 (-8.47)	0.18 (5.45)	0.96
6	0.26 (2.97)	0.99 (43.30)	0.74 (21.20)	0.09 (2.38)	-0.18 (-7.21)	0.26 (-7.21)	0.95
7	0.41 (5.17)	0.98 (46.66)	0.72 (22.36)	0.04 (1.08)	-0.15 (-6.61)	0.34 (9.63)	0.95
8	0.41 (4.10)	0.98 (37.53)	0.66 (16.47)	0.07 (1.63)	-0.19 (-6.62)	0.34 (7.73)	0.93
9	0.41 (4.49)	0.95 (39.26)	0.65 (17.67)	0.03 (0.66)	-0.18 (-6.57)	0.39 (9.50)	0.93
10 (peripheral)	0.43 (5.46)	0.97 (46.48)	0.51 (16.07)	0.02 (0.58)	-0.17 (-7.45)	0.63 (18.10)	0.94
			01/2000 - 12/2018				
1 (central)	0.55 (6.42)	0.84 (34.47)	0.47 (17.04)	0.14 (5.21)	-0.25 (-13.32)	-0.47 (-19.36)	0.96
2	0.36 (4.74)	0.96 (43.3)	0.59 (23.75)	0.23 (9.02)	-0.22 (-12.50)	-0.19 (-8.52)	0.97
3	0.43 (5.14)	0.96 (39.76)	0.65 (24.25)	0.23 (8.23)	-0.19 (-10.15)	-0.07 (-3.02)	0.96
4	0.25 (3.44)	1.01 (48.91)	0.63 (27.09)	0.25 (10.51)	-0.17 (-10.78)	0.04 (1.82)	0.97
5	0.24 (3.33)	1.02 (49.23)	0.67 (28.89)	0.27 (11.45)	-0.14 (-8.96)	0.11 (5.54)	0.96
6	0.16 (2.02)	1.03 (45.44)	0.67 (26.52)	0.25 (9.56)	-0.15 (-8.62)	0.21 (9.33)	0.95
7	0.22 (2.95)	0.99 (46.60)	0.63 (26.71)	0.25 (10.44)	-0.16 (-9.83)	0.25 (-9.83)	0.96
8	0.20 (2.35)	0.99 (40.85)	0.63 (23.21)	0.19 (6.93)	- 0.17 (-8.77)	0.33 (13.62)	0.94
9	0.23 (2.72)	0.97 (40.17)	0.60 (22.26)	0.22 (8.13)	-0.16 (-8.50)	0.36 (14.83)	0.94
10 (peripheral)	0.55 (6.42)	0.85 (34.47)	0.47 (17.04)	0.15 (5.21)	-0.25 (-13.32)	0.53 (21.77)	0.91

Table 13: **Estimating the 3-Factor Fama-French model augmented with the interconnected factor for the 5-by-5 double sorted size-value portfolios.**
Parameter of the 3 Factor (Fama and French (1993)) model (eq.14) augmented with the interconnectedness factor (pmc) estimated for the 25 size-value double-sorted portfolios on monthly returns after subtracting the risk-free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the interconnectedness portfolio as pmc. Monthly data for the market, size and value factor portfolios are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{pmc}$	R^2_{adj}
s1b1	-0.88 (-4.32)	1.19 (21.30)	1.21 (17.52)	-0.24 (-3.33)	0.20 (3.30)	0.74
s1b2	-0.23 (-1.61)	1.09 (27.88)	1.06 (21.81)	0.05 (1.08)	0.19 (4.52)	0.81
s1b3	-0.03 (-0.29)	1.00 (31.36)	0.90 (22.74)	0.26 (6.52)	0.16 (4.59)	0.83
s1b4	0.10 (1.07)	0.94 (35.30)	0.85 (25.68)	0.38 (11.18)	0.21 (7.29)	0.86
s1b5	0.17 (1.36)	1.02 (29.74)	0.87 (20.42)	0.49 (11.39)	0.31 (8.37)	0.80
s2b1	-0.10 (-0.92)	1.09 (35.77)	1.03 (27.34)	-0.32 (-8.28)	-0.25 (-7.38)	0.91
s2b2	0.14 (1.61)	1.02 (43.62)	0.85 (29.27)	0.18 (5.90)	-0.14 (-5.45)	0.91
s2b3	0.23 (2.92)	0.96 (44.68)	0.75 (28.03)	0.46 (16.98)	-0.13 (-5.38)	0.91
s2b4	0.13 (1.99)	0.94 (51.29)	0.74 (32.36)	0.66 (28.30)	-0.11 (-5.39)	0.93
s2b5	0.10 (-1.29)	1.12 (50.28)	0.87 (31.67)	0.92 (32.63)	-0.09 (-3.56)	0.93
s3b1	0.09 (0.88)	1.06 (37.07)	0.75 (21.06)	-0.38 (-10.53)	-0.24 (-7.72)	0.91
s3b2	0.15 (1.71)	1.04 (41.99)	0.56 (18.01)	0.25 (7.97)	-0.12 (-4.29)	0.89
s3b3	0.08 (1.02)	0.99 (43.45)	0.47 (16.57)	0.47 (16.32)	-0.12 (-4.67)	0.89
s3b4	0.11 (1.36)	0.98 (42.52)	0.46 (16.14)	0.66 (22.62)	-0.08 (-3.18)	0.89
s3b5	0.19 (1.82)	1.07 (36.67)	0.57 (15.71)	0.89 (23.95)	-0.16 (-4.87)	0.86
s4b1	0.28 (3.24)	1.04 (44.80)	0.41 (14.11)	-0.33 (-11.04)	-0.20 (-7.86)	0.92
s4b2	0.03 (0.30)	1.08 (41.41)	0.16 (5.00)	0.27 (8.29)	-0.06 (-1.96)	0.86
s4b3	-0.10 (-1.00)	1.10 (39.67)	0.19 (5.45)	0.47 (13.52)	-0.01 (-0.18)	0.85
s4b4	0.04 (0.45)	1.03 (41.60)	0.15 (4.90)	0.56 (17.73)	-0.02 (-0.74)	0.86
s4b5	-0.03 (-0.22)	1.13 (35.57)	0.27 (6.86)	0.86 (21.34)	-0.18 (-5.27)	0.84
s5b1	0.16 (2.56)	1.03 (60.72)	-0.08 (-3.81)	-0.30 (-13.97)	-0.11 (-5.83)	0.94
s5b2	0.07 (0.98)	1.03 (49.82)	-0.10 (-3.88)	0.18 (6.79)	-0.04 (-1.36)	0.90
s5b3	-0.00 (-0.03)	1.03 (46.00)	-0.18 (-6.40)	0.39 (13.81)	0.04 (1.49)	0.87
s5b4	-0.15 (-1.68)	1.02 (42.04)	-0.13 (-4.17)	0.64 (20.58)	-0.01 (-0.55)	0.86
s5b5	-0.04 (-0.35)	1.13 (34.19)	-0.08 (-1.98)	0.80 (18.92)	-0.04 (-1.12)	0.81

Table 14: **Estimating the 3-Factor Fama-French model augmented with the interconnectedness factor for industrial portfolios.** Parameter of the 3 Factor (Fama and French (1993)) model (eq.14) augmented with the interconnectedness factor (pmc) estimated for the 12 industrial portfolios proposed by E. Fama and K. French. The model is estimated using monthly returns after subtracting the risk free rate. The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the interconnectedness portfolio as pmc. Monthly data for the market, size and value factor portfolios as well as data for the industrial portfolios are obtained by the Kenneth French's website.
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

Portfolio	$\hat{a}_p$	$\hat{\beta}_{mk}$	$\hat{\beta}_{smb}$	$\hat{\beta}_{hml}$	$\hat{\beta}_{pmc}$	R^2_{adj}
No Durable	-0.10 (-0.91)	0.93 (30.38)	0.55 (14.61)	0.39 (10.07)	0.10 (2.93)	0.79
Durable	-0.52 (-3.60)	1.19 (30.07)	0.84 (17.14)	0.53 (10.57)	0.11 (2.50)	0.80
Manufacturing	-0.25 (-2.35)	1.12 (38.88)	0.77 (21.39)	0.46 (12.47)	0.08 (2.58)	0.87
Energy	-1.09 (-3.41)	1.25 (14.24)	0.55 (5.02)	0.68 (6.1)	0.36 (3.78)	0.40
Chemistry	-0.25 (-1.92)	1.12 (31.84)	0.53 (12.16)	0.46 (10.26)	0.13 (3.28)	0.79
Business Equipment	0.19 (1.09)	1.15 (24.14)	1.18 (19.79)	-0.40 (-6.62)	-0.04 (-0.69)	0.81
Telecom	0.06 (0.30)	1.19 (20.29)	0.81 (11.10)	-0.12 (-1.54)	-0.01 (-0.17)	0.68
Utilities	0.35 (2.82)	0.53 (15.47)	-0.04 (-0.96)	0.33 (7.61)	0.04 (1.11)	0.42
Shops	-0.24 (-1.78)	1.04 (28.29)	0.78 (16.96)	0.38 (7.97)	0.09 (2.15)	0.79
Money	-0.06 (-0.57)	0.88 (33.69)	0.44 (13.55)	0.62 (18.59)	0.14 (4.99)	0.81
Healthcare	0.04 (0.21)	1.17 (24.72)	1.15 (19.51)	-0.22 (-3.76)	0.31 (6.007)	0.79
Other	-0.34 (-3.00)	1.08 (34.85)	0.83 (21.59)	0.28 (7.11)	0.14 (4.04)	0.85

Table 15: **Modelling the returns of Betting-against-the-Beta factor portfolio.**
Parameter of various models being estimated on monthly with the returns of Betting-against-the-Beta (BaB) factor portfolios used as the dependent variable. CAPM describes the model in eq. 8, pmc is a single factor model including a constant and the interconnectedness factor (pmc), 3F is three Fama-French model (eq. 9), 3F+pmc is three Fama-French model (eq. 9) augmented with the interconnectedness factor (pmc), 5F is five Fama-French model (eq. 10), 5F+pmc is five Fama-French model (eq. 10) augmented with the interconnectedness factor (pmc), 5F+iml+umd is five Fama-French model (eq. 10) augmented with the momentum and liquidity factors and 5F+iml+umd+pmc is five Fama-French model (eq. 10) augmented with the momentum, liquidity and interconnectedness factor.
The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the operetional profitability as rmw, the investment style as cma, the momentum portfolio as umd, the liquidity portfolio as iml and the interconnectedness factor as pmc. Monthly data for the market, size, value, operational profitability and investment style factor are obtained by the Kenneth French's website. Data for momentum factor portfolio are obtained from the CRSP database and data for the traded liquidity factor are obtained from Pastor L. (2019).
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

	CAPM	**pmc**	**CAPM+pmc**	**3F**	**3F+pmc**	**5F**	**5F+pmc**	**5F+iml+umd**	**5F+iml+umd+pmc**
$\hat{a}_p$	1.07 (6.34)	0.64 (4.38)	0.52 (3.438)	0.89 (5.52)	0.34(2.43)	0.5 (3.52)	0.07 (0.53)	0.40(2.57)	0.02 (0.30)
$\hat{\beta}_{mk}$	-0.17 (-4.31)		0.12 (3.07)	-0.09 (-2.30)	0.22 (5.90)	0.02 (0.58)	0.30 (8.35)	0.06 (1.6)	0.29 (8.20)
$\hat{\beta}_{smb}$				0.002 (0.03)	-0.17 (-3.56)	0.21 (3.72)	0.04 (0.84)	0.18 (3.34)	0.04 (0.90)
$\hat{\beta}_{hml}$				0.44 (7.6)	0.38 (7.82)	0.24 (3.35)	0.25 (4.33)	0.36 (5.14)	0.28 (4.64)
$\hat{\beta}_{rmw}$						0.65 (8.89)	0.60 (10.11)	0.59 (8.3)	0.59 (9.88)
$\hat{\beta}_{cma}$						0.33 (3.17)	0.18 (2.038)	0.24 (2.37)	0.16 (1.86)
$\hat{\beta}_{umd}$								0.07 (1.74)	0.06 (1.91)
$\hat{\beta}_{iml}$								0.22 (6.53)	0.05 (1.43)
$\hat{\beta}_{pmc}$		0.51 (13.74)	0.58 (13.26)		0.61 (14.64)		0.58 (15.38)		0.55 (13.36)
R^2_{adj}	0.037	0.29	0.31	0.15	0.43	0.29	0.53	0.35	0.54

Table 16: **Modelling the returns of the interconnectedness factor portfolio.**
Parameter of various models being estimated on monthly returns with the the interconnectedness (pmc) factor portfolios used as the dependent variable. CAPM describes the model in eq. 8, bab is a single factor model including a constant and the bet-against-the-beta factor, 3F is three Fama-French model (eq. 9), 3F+bab is three Fama-French model (eq. 9) augmented with the bet-against-the-beta factor, 5F is five Fama-French model (eq. 10), 5F+bab is five Fama-French model (eq. 10) augmented with the bet-against-the-beta factor, 5F+iml+umd is five Fama-French model (eq. 10) augmented with the momentum and liquidity factors and 5F+iml+umd+bab is five Fama-French model (eq. 10) augmented with the momentum, liquidity and the bet-against-the-beta factor.
The market portfolio is indicated as mk, the size portfolio as smb, the value portfolio as hml, the operetional profitability as rmw, the investment style as cma, the momentum portfolio as umd, the liquidity portfolio as iml and the betting-against-beta factor as bab. Monthly data for the market, size, value, operational profitability and investment style factor are obtained by the Kenneth French's website. Data for momentum factor portfolio are obtained from the CRSP database and data for the traded liquidity factor are obtained from Pastor L. (2019).
Analysis covers the period January 1981 - December 2018. Numbers in the parenthesis report the t-statistics value. Alphas are in percent.

	CAPM	**bab**	**CAPM+bab**	**3F**	**3F+bab**	**5F**	**5F+bab**	**5F+iml+umd**	**5F+iml+umd+bab**
$\hat{a}_p$	0.96 (6.23)	0.09 (0.60)	0.44 (3.25)	0.91 (6.06)	0.44 (3.42)	0.81 (5.23)	0.49 (3.86)	0.60 (4.32)	0.40 (3.46)
$\hat{\beta}_{mk}$	-0.49 (-14.07)		-0.41 (-13.60)	-0.51 (-14.40)	-0.47 (-15.79)	-0.47 (-12.34)	-0.49 (-15.65)	-0.42 (-11.88)	-0.45 (-15.02)
$\hat{\beta}_{smb}$				0.28 (5.38)	0.28 (6.51)	0.30 (5.14)	0.17 (3.59)	0.25 (4.79)	0.16 (3.51)
$\hat{\beta}_{hml}$				0.11 (1.99)	-0.13 (-2.66)	-0.02 (-0.27)	-0.16 (-2.72)	0.15 (2.22)	-0.04 (-0.61)
$\hat{\beta}_{rmw}$						0.09 (1.17)	-0.30 (-4.61)	0.002 (0.028)	-0.31 (-4.89)
$\hat{\beta}_{cma}$						0.27 (2.56)	0.07 (0.86)	0.15 (1.48)	0.02 (0.25)
$\hat{\beta}_{umd}$								0.30 (8.95)	0.18 (6.16)
$\hat{\beta}_{iml}$								0.04 (0.98)	0.002 (0.066)
$\hat{\beta}_{bab}$		0.58 (13.74)	0.48 (13.26)		0.53 (12.64)		0.59 (15.38)		0.52 (13.37)
R^2_{adj}	0.30	0.29	0.50	0.347	0.56	0.36	0.58	0.46	0.61