Chapter 12
Empirical Analysis of Market Connectedness as a Risk Factor for Explaining Expected Stock Returns

Shijie Deng, Min Sim, and Xiaoming Huo

12.1 Introduction

Analyzing financial asset returns by identifying market-wide risk drivers and common firm-level characteristics that contribute to the explanation of expected asset returns has evolved into one major research field in the development of the modern asset pricing theory. The Capital Asset Pricing Model (CAPM) developed by Treynor (1962, 1961, Market value, time, and risk, "unpublished"),[1] Sharpe (1964), Lintner (1965a,b), and Mossin (1966) initiated this strand of research, which is referred to as the single-factor model. The single-factor model identifies a single index, or a market portfolio, as the sole driver of the return of financial assets and decomposes individual asset return risk into systematic and idiosyncratic components.

Empirical studies based on the single-factor model report mixed findings in validating CAPM as a positive economic model. Early studies such as Black et al. (1972) and Fama and MacBeth (1973) find evidence supporting a linear relationship between the average asset returns. A quantity measuring how asset returns covary with the return of market portfolio, termed market beta, is found when the data period is long. However, subsequent studies such as Fama and French (1992) and Davis (1994) provide only weak evidence in supporting CAPM. Roll (1977) points out that the CAPM cannot be empirically tested conclusively because of the difficulty in measuring the risk-return characteristics of the market portfolio.

[1] See French (2003) for details of these references.

S. Deng (✉) • M. Sim • X. Huo
Steward School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA, USA
e-mail: deng@gatech.edu

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Roll and Ross (1994), Kandel and Stambaugh (1995) demonstrate that even very small deviations from the efficient portfolio can yield the linear relationship between risk and expected returns insignificant.

The inconclusive empirical testing results of the single-factor model combined with evidence on that firm-level fundamental variables such as earnings-to-price (E/P) ratio (Basu (1977)) predict higher asset returns than those predicted by market beta prompt that the market beta alone may not be able to explain the cross-sectional variation in the asset returns. This leads to a growing research literature on extending the single-factor CAPM to a multi-factor model by using firm-level fundamental variables such as E/P ratio (Basu (1977)) and market value to book value ratio (e.g., Rosenberg et al. (1985), De Bondt and Thaler (1987)), market-level variables such as price momentum (Jegadeesh and Titman (1993)), and macroeconomic variables such as trading liquidity (Paster and Stambaugh (2003)) to explain the expected asset returns.

Even with the extended multi-factor models such as Rosenberg (1974), Roll and Ross (1980), and Fama and French (1993), empirical studies with equity market data still do not generate clear-cut positive results. Researchers are constantly searching for alternative risk factors that may have stronger explanatory variables for the cross-sectional asset returns. Paster and Stambaugh (2003) is one such example in which the authors show that individual stock's sensitivity to market level liquidity innovation can be a significant driver for asset return variations. In a similar vein, Sim et al. (2014) show that individual stock's sensitivity to the overall market connectedness forms a promising risk factor that helps to explain the expected stock returns.

In this article, we introduce a quantitative measure for the connectedness of financial markets as proposed in Sim et al. (2014). We demonstrate via empirical tests using a two-factor model that the market connectedness measure holds explanatory power the expected stock returns. The remainder of this article is organized as follows. Section 12.2 presents the classical approaches for empirically testing CAPM and its multi-factor extensions. The description of the alternative measure for market connectedness and its construction are given in Sect. 12.3. Empirical tests on whether the market connectedness corresponds to a new source of systematic risk driving the stock returns are performed in Sect. 12.4. Finally, we present results and conclude in Sect. 12.5.

12.2 CAPM and the Multi-Factor Asset Pricing Model

Let R_s, R_M, R_f denote the returns of an asset s, the market portfolio M, and the risk-free asset, respectively. CAPM specifies a linear relationship between the return of any individual financial asset and that of a market portfolio. Namely,

$$E[R_s] = R_f + \beta_{s,M}(E[R_M] - R_f) \tag{12.1}$$

where $E[\cdot]$ denotes expected value, and $\beta_{s,M} \equiv \frac{Cov(R_s,R_M)}{\sigma_M^2} = \rho_{s,M}\frac{\sigma_s}{\sigma_M}$ is the market beta of asset s measuring the systematic risk exposure of the excess return of s to the risk of the market portfolio M. In the definition of $\beta_{s,M}$, σ_R and $\rho_{s,M}$ denote, respectively, the volatility of R and the correlation coefficient between the returns R_s and R_M.

12.2.1 Empirical Testing of CAPM

Equation (12.1) is often referred to as the Security Market Line (SML) and it leads to the usual form of the testing hypothesis of the empirical investigation of CAPM.

As CAPM is a single-period *ex ante* model and asset returns are not known in *ex ante*, researchers use *ex post* returns to test CAPM instead. Specifically, market beta of asset s is estimated through the following equation using historical data:

$$r_{s,t} - r_{f,t} = a_s + \beta_{s,M}(r_{M,t} - r_{f,t}) + \epsilon_{s,t}, \tag{12.2}$$

where in each period a_s is a constant return earned by asset s, $r_{s,t}$ is the return of asset s at time t, $r_{f,t}$ is the risk-free rate at time t, and $\epsilon_{s,t}$ is the noise in the realized return of s. The estimated market beta $\beta_{s,M}$ is used as explanatory variable to test the cross-sectional equation (12.3).

$$r_{s,t} = \alpha_0 + \alpha_1\beta_{s,M} + \eta_{s,t}, \tag{12.3}$$

where α_0 is the expected return of a risk-free asset (or, a zero-beta portfolio), α_1 is the expected excess return of the market portfolio (or, the market risk premium), and $\eta_{s,t}$ is the noise term. If the cross-sectional test yields a statistically significant value of α_1, then the validity of CAPM is supported.

While initial empirical research such as Black et al. (1972), Fama and MacBeth (1973) found supporting evidence of high beta assets tend to generate high level of returns that is consistent with the linear relationship in (12.2), later research working with a larger amount of historical data (e.g., Fama and French (1992), Davis (1994)) found that the empirical evidence is rather weak. Further evidence on the market portfolio falling short in fully explaining asset returns such as Basu (1977), Banz (1981), Rosenberg et al. (1985), Jegadeesh and Titman (1993) sparks a vast body of research on extending the CAPM model, in the spirit of the arbitrage-pricing model of Ross (1976), to a multi-factor model as proposed by Fama and French (1993, 1996), Carhart (1997), Frankel and Lee (1998), Paster and Stambaugh (2003), among others.

12.2.2 Multi-Factor Asset Return Model

In a general multi-factor asset return model, the excess return of asset s (namely, the amount in excess to the risk-free return rate r_f), denoted by $\bar{r}_s$, is attributed to its exposure to a set of N_c non-diversified systematic risk factors. Specifically, we have

$$\bar{r}_s = \alpha + \sum_{c=1}^{N_c} \beta_{s,c}\bar{f}_c + \epsilon_s, \tag{12.4}$$

where $\bar{f}_c$ is the excess return of the c^{th} systematic risk factor, ϵ_s is the asset-specific residual after removing the impact of all factors from the excess return of asset s. It represents the diversifiable risk that is specific to asset s, and $\beta_{s,c}$ measures the exposure of the excess return of asset s to the systematic risk-factor c and is termed *factor beta*.

Various types of observable variables have been proposed as alternative systematic risk factors. These include firm-level variables (e.g., earnings-to-price, book-to-market, market capitalization level), market-level variables such as price momentum, and macro-economics level variables such as liquidity. There are also pure statistical factors obtained through analyzing the covariance matrix of asset returns directly (see Connor and Korajczyk (2010) for an extensive review of the risk factor models).

12.3 Market-Connectedness and Systematic Risk in Asset Returns

As the scope of financial markets has been expanded tremendously over the recent decades through introductions of vast amounts of stocks and diverse derivatives products, a question arises as to whether this yields a more expanded investment opportunity set for investors in general.

Anecdotal evidences indicate that the levels of interactions within and among financial markets have increased significantly over the last decade. Thus the expanding landscape of financial markets may not result in a much expanded investment opportunity set. In fact, markets with highly correlated traded assets, even with the total market capitalization being large, do not necessarily provide diverse investment opportunities to market participants. Market participants must comprehend the inter-related structures in markets in order to truly assess the investment opportunity set so that they can practice portfolio diversification and risk managements effectively.

12.3.1 Alternative Measures for Financial Market Connectedness

The research strand on the study of market connectedness[2] has been growing and focusing on quantifying the level of association in financial assets in order to assess overall market structures from the perspective of a graph or a network. For example, Billio et al. (2012) and Diebold and Yilmaz (2011) construct their connectedness measures in financial institutions to measure the level of systemic risk during the global recession period in 2007–2008 and provide empirical evidence that their measures are related to the cycle of economy.

In analyzing the connectedness of financial markets and its impact on the investment opportunity set, Sim et al. (2014) propose a market connectedness measure, termed modularity, to quantify the level of connectedness of financial markets. They take a different approach to quantify the market connectedness through analyzing *the clustering tendency* in stock markets.

According to recent studies, the cluster property, where entities with similar characteristics tend to form a subgroup or a cell, is one of the most evident and important structural properties in financial markets. Materassi and Innocenti (2009) provide empirical evidence that the major stocks in the US can be drawn in tree structure, a special case of cluster structure, where branches of the tree connect the highly correlated stocks together. Pojarliev and Levich (2010) classify foreign exchange investing funds into two groups and proposed a few crowdedness measures for co-movement tendency of market participants. Chandrasekaran et al. (2012) conduct an empirical analysis on the US stock market through a hidden Gaussian graphical model, which shows that the clustering tendency across the universe of stocks is observable even after eliminating a few common drivers of the stock market.

Following the clustering studies in Materassi and Innocenti (2009) and Chandrasekaran et al. (2012), Sim et al. (2014) classify the correlation elements in stock markets into two groups: one group containing stocks that tend to be highly correlated with each other and the other group containing stocks that fluctuate along with the flucturation of the cycle of economy. Connectedness measures are then constructed by measuring the relative difference between the respective average correlations of the two groups. The relationship between the proposed connectedness measure and the movements of individual stocks are further explored.

[2]The development of this line of study is largely grounded in the development of graph theory or network theory that are actively studied in the various disciplines such as combinatorics, computer science, physics, and (bio)-statistics.

12.3.2 Market Connectedness Measure: Modularity

This section offers a bottom-to-top approach for constructing the modularity measure using Pearson's pairwise correlation. Let $C(i,j)$ denote Pearson's pairwise correlation between two stock returns. Namely,

$$C(i,j) \equiv \rho_{i,j} = \frac{Cov(r_i, r_j)}{std.dev.(r_i)std.dev.(r_j)} \tag{12.5}$$

where r_i and r_j are the returns of stock i and j, respectively. Using pairwise correlations as a building block, the *connectedness between two groups of stocks* is defined as follows:

$$C(A,B) := \text{Mean}\left(\{C(i,j)|\forall i \in A, \forall j \in B, i \neq j\}\right) \tag{12.6}$$

where A and B are two groups of stocks, and $Mean(\cdot)$ calculates the mean of elements in a set. Note that the groups A and B are allowed to have overlaps (or, even be identical to each other). The condition $i \neq j$ excludes trivial self-correlations for overlapping stocks.

Let V denote the universe of stocks considered for investment in the market. A *partition P* of V is defined as $P = \{V_1, V_2, \ldots, V_k\}$, where $V = \bigcup_{c=1}^{k} V_c$, $V_i \cap V_j = \emptyset$, and V_i denotes the i^{th} sub-group of stocks. Each sub-group is termed a *cell*. *Clustering* or *cluster analysis* on correlation matrix is a task of finding the best partition P for V such that the pairwise correlation of returns between stocks within each cell are generally higher than the return correlations of stocks that belong to different cells.

The connectedness of stock returns in universe V is defined with respect to a given partition P. Specifically, the *inner-sector connectedness (INSC)* is the average of all pairwise correlations within the cells in the partition P,

$$\text{INSC}(P) := \text{Mean}\left(\bigcup_{c=1}^{k}\{C(i,j)|(i,j) \in (V_c, V_c), i \neq j\}\right). \tag{12.7}$$

Similarly, the *inter-sector connectedness (ITSC)* is defined as the average of all correlations across the cells in the partition P. Namely,

$$\text{ITSC}(P) := \text{Mean}\left(\bigcup_{c_1=1}^{k-1}\bigcup_{c_2=c_1+1}^{k}\{C(i,j)|(i,j) \in (V_{c_1}, V_{c_2})\}\right). \tag{12.8}$$

If the partition P exhibits a prominent cluster structure in the asset return correlation matrix, then INSC(P) is expected to be much higher than ITSC(P), meaning that the returns of assets in each cell of P are much more dependent on each other in their own cell than they are with the returns of stocks in other cells. Therefore, a high

INSC(P) in conjunction with a low ITSC(P) implies that the partition P represents a very prominent clustering of asset returns in universe V while a low INSC(P) combined with a high ITSC(P) implies the contrary.

The modularity of the asset returns in universe V with respect to the partition P is defined as the difference between INSC(P) and ITSC(P) with an intuitive meaning of capturing the significance of a clustering structure represented by partition P. Namely,

$$\mathrm{MOD}(P) := \mathrm{INSC}(P) - \mathrm{ITSC}(P). \tag{12.9}$$

Clearly, identifying a clustering structure among the myriad of financial assets traded in the markets, if such a structure exists, is a first important step towards the understanding of connectedness of various financial markets. Sim et al. (2014) adopt the *Modulated Modularity Clustering (MMC)* method proposed by Stone and Ayroles (2009) for detecting the clustering structure in the financial security returns.

12.4 Modularity Index as a Systematic Risk Factor: Empirical Analysis

In this section, we take 60 major stocks from the top of the Fortune 500 U.S. firms, ranked by their operating revenue in 2011, as the universe of investment opportunities and report the clustering structure obtained by applying the MMC method. Pairwise return correlations are calculated based on daily return data from the The Center for Research in Security Prices (CRSP) Database provided by Wharton Research Data Services (WRDS).

Using the identified clusters as a partition, the market connectedness measures and the modularity index are computed. We demonstrate that one may construct portfolios using US equities based on their sorted beta with respect to the modularity index and generate excess returns, which is greater than what is predicted by a CAPM model.

12.4.1 Clusters of Asset Returns over a Long Period

The pairwise return correlations of the 60 stocks (full-list given in Table 12.1) are computed using the daily close price in CRSP from 1/1/2002 to 12/31/2011 to form a sample correlation matrix. Twelve clusters (or, cells) are obtained after applying the MMC algorithm to this sample correlation matrix. The identified clusters are given in Fig. 12.1. Note that the partitioning clusters identified by the MMC method

Table 12.1 List of 60 stocks chosen based on 2011 Fortune 500 ranking

Cell	Ticker	Company name	Revenues ($ millions) (in 2011)	SIC code	SIC description
1	CVS	CVS Caremark	107,750	5912	Retail-Drug Stores and Proprietary Stores
	WAG	Walgreen	72,184	5912	Retail-Drug Stores and Proprietary Stores
	SYY	Sysco	39,324	5141	Wholesale-Groceries, General Line (merchandise)
	ESRX	Express Scripts Holding	46, 128	8093	Services-Specialty Outpatient Facilities, NEC
	KFT	Kraft Foods	54,365	2052	Cookies & Crackers
	WLP	WellPoint	60,711	6324	Hospital & Medical Service Plans
2	KO	Coca-Cola	46,542	2086	Bottled & Canned Soft Drinks & Carbonated Waters
	PEP	PepsiCo	66,504	2086	Bottled & Canned Soft Drinks & Carbonated Waters
	PG	Procter & Gamble	82,559	2841	Soap and Other Detergents
	PFE	Pfizer	67,932	2834	Pharmaceutical Preparations
	JNJ	Johnson & Johnson	65,030	2834	Pharmaceutical Preparations
	MRK	Merck	48,047	2834	Pharmaceutical Preparations
3	GE	General Electric	147,616	3511	Turbines and Turbine Generator Sets
	DOW	Dow Chemical	59,985	2821	Plastic Materials, Synth Resins & Nonvulcan Elastomers
	JCI	Johnson Controls	40,833	2531	Public Bldg & Related Furniture
	MET	MetLife	70,641	6311	Life Insurance
	PRU	Prudential Financial	49,045	6311	Life Insurance
4	XOM	Exxon Mobil	452,926	2911	Petroleum Refining
	COP	ConocoPhillips	237,272	2911	Petroleum Refining
	CVX	Chevron	245,621	2911	Petroleum Refining
	MRO	Marathon Petroleum	73,645	2911	Petroleum Refining
	CAT	Caterpillar	60,138	3531	Construction Machinery & Equip

Cell	Ticker	Company name	Revenues ($ millions) (in 2011)	SIC code	SIC description
5	MSFT	Microsoft	69,943	7370	Services-Computer Programming, Data Processing, Etc.
	DELL	Dell	62,071	3570	Computer & office Equipment
	IBM	International Business Machines	106, 916	3571	Electronic Computers
	AAPL	Apple	108,249	3571	Electronic Computers
	UTX	United Technologies	58, 190	3724	Aircraft Engines & Engine Parts
	HPQ	Hewlett-Packard	127,245	3571	Electronic Computers
	INTC	Intel	53,999	3679	Electronic Components, NEC
	CSCO	Cisco Systems	43,218	3674	Semiconductors & Related Devices
	INTL	INTL FCStone	75,498	6211	Security Brokers, Dealers & Flotation Companies
	AMZN	Amazon.com	48,077	7370	Services-Computer Programming, Data Processing, Etc.
6	CAH	Cardinal Health	102,644	5122	Wholesale-Drugs, Proprietaries & Druggists' Sundries
	MCK	McKesson	112,084	5122	Wholesale-Drugs, Proprietaries & Druggists' Sundries
	ABC	AmerisourceBergen	80,218	5122	Wholesale-Drugs, Proprietaries & Druggists' Sundries
	UNH	UnitedHealth Group	101,862	6324	Hospital & Medical Service Plans
7	WFC	Wells Fargo	87,597	6021	National Commercial Banks
	JPM	J.P. Morgan Chase & Co.	110,838	6712	Bank Holding Companies
	BAC	Bank of America Corp.	115,074	6021	National Commercial Banks
	AIG	American International Group	71,730	6331	Fire, Marine & Casualty Insurance
	C	Citigroup	102,939	6021	National Commercial Banks
8	SUN	Sunoco	45,765	2911	Petroleum Refining
	VLO	Valero Energy	125,095	2911	Petroleum Refining
	EPD	Enterprise Products Partners	44,313	4922	Natural Gas Transmission

(continued)

Table 12.1 (continued)

9	TGT	Target	69,865	5331	Retail-Department Stores
	WMT	Wal-Mart Stores	446,950	5331	Retail-Department Stores
	LOW	Lowe's	50,208	5211	Retail-Lumber & Other Building Materials Dealers
	HD	Home Depot	70,395	5211	Retail-Lumber & Other Building Materials Dealers
	BBY	Best Buy	50,272	5731	Retail-Radio, TV & Consumer Electronics Stores
	COST	Costco Wholesale	88,915	5330	Food & Drug Retailers
	UPS	United Parcel Service	53,105	4215	Courier Services, Except By Air industry
10	ADM	Archer Daniels Midland	80,676	2075	Soybean Oil Mills
	BA	Boeing	68,735	3721	Aircraft
	LMT	Lockheed Martin	46,692	3764	Space Propulsion Units and Parts
11	F	Ford Motor	136,264	3711	Motor Vehicles & Passenger Car Bodies
	DIS	Walt Disney	40,893	7996	Services-Amusement Parks
	VZ	Verizon Communications	110,875	4813	Telephone Communications (No Radiotelephone)
	T	AT&T	126,723	4813	Telephone Communications (No Radiotelephone)
12	KR	Kroger	90,374	5411	Retail-Grocery Stores
	SWY	Safeway	43,630	5411	Retail-Grocery Stores

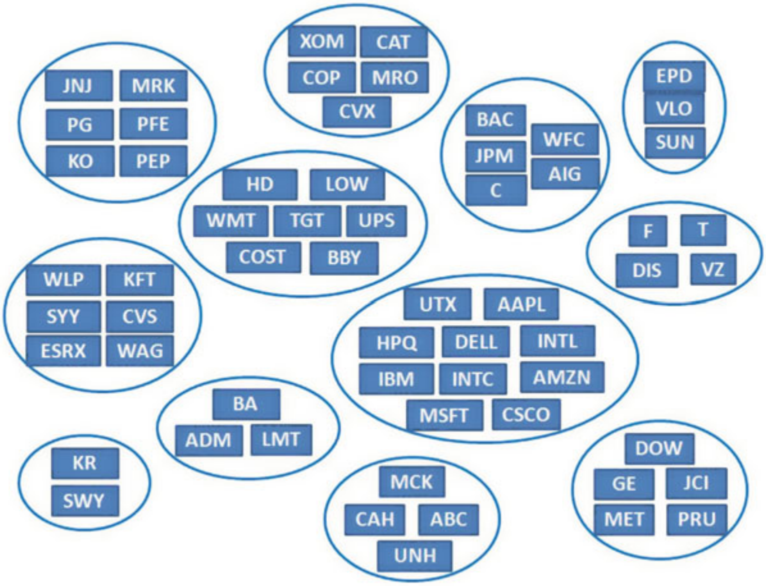

Fig. 12.1 Cluster analysis with 10 years returns of 60 major stocks by MMC algorithm

do not exactly match with those categorized by the Standard Industry Classification (SIC) codes (see Table 12.1). Based on this cluster partition, a modularity index, MOD, is constructed from Eqs. (12.7), (12.8) and (12.9).

12.4.2 Modularity: A Systematic Risk Factor

To empirically test whether the modularity index MOD is a valid systematic risk factor, we conjecture that the decile portfolio sorted by the individual stock's sensitivity to MOD would show significant differences in return. We follow a similar regression procedure as that used by Fama and MacBeth (1973) to estimate the beta of each stock with respect to MOD_t over time based on a two-factor model (namely, setting $N_c = 2$ in model (12.4)). The detailed steps of the procedure are described in Sim et al. (2014). After getting the beta-to-MOD of each stock, we construct the decile portfolios based on sorted values of beta-to-MOD, where the top decile portfolio consists of stocks with the least beta-to-MOD values.

Using data from the period of January 1992 to December 2011, Table 12.2 shows that beta-to-MOD sorted decile portfolio creates systematic return difference that are not explained by CAPM. The first row presents the annualized return and standard deviation of each decile portfolio. The last column corresponds to the difference of 1-portfolio and 10-portfolio that is equivalent to the net zero investment portfolio where investors buy the first decile and sell the last decile in

Table 12.2 Returns and alphas of the decile portfolios (January 1992–December 2011)

	1	2	3	4	5	6	7	8	9	10	'1–10'
Return (p.a.)	13.99	10.23	10.29	11.41	10.06	8.21	8.48	11.11	7.72	6.4	7.59
s.d. (p.a.)	20.94	17.1	14.29	14.25	14.45	14.78	14.99	15.67	18.5	20.9	14.8
CAPM alpha	4.25	1.43	2.51	3.54	2	0.25	0.35	2.6	−1.69	−3.66	7.92
(t-statistics)	(1.66)	(0.79)	(1.58)	(2.39)	(1.46)	(0.15)	(0.23)	(1.84)	(−0.94)	(−1.66)	(2.38)

Fig. 12.2 Cumulative return on enhancement scenarios with MOD_P

Table 12.3 Performance of enhanced market index portfolio (January 1992–December 2011)

	MKT	MKT+10 % MOD_s	MKT+20 % MOD_s
Return (p.a.)	8.94 %	9.69 %	10.45 %
Std (p.a.)	15.46 %	15.44 %	15.57 %
SR (monthly)	0.109	0.123	0.136

the same amount. The second row present the level of alphas (and the t-statistics for the null hypothesis of alphas being zero) when fitting the excess returns of the decile portfolios to CAPM. Clearly, the return of the 1–10 portfolio reported in Table 12.2 cannot be fully attributed to that of the market portfolio in CAPM.

Indeed, the 1–10 portfolio based on the MOD factor enlarges the investment opportunity set for investors. Figure 12.2 illustrates that, if one adds different weights, such as 10 % and 20 %, of the 1–10 portfolio to the proxy market portfolio, then the resulting overall portfolio outperforms the proxy market portfolio. The corresponding Sharpe ratios are higher than that of the proxy market portfolio (see the last row of Table 12.3).

12.5 Conclusion

In this article, a quantitative measure for quantifying the connectedness of financial markets is briefly introduced. Through empirical tests, we demonstrate that this alternative measure for market connectedness, termed modularity in Sim et al. (2014), can act as a new risk factor for explaining the expected stock returns under the multi-factor asset pricing model framework. Using the U.S. equity market data from 1992 to 2011, decile portfolio analysis based on the beta-to-modularity indeed generates significant excess returns that cannot be explained by CAPM. Empirical tests also reveal that the properly constructed decile portfolios based on asset return sensitivity to market connectedness enhances investment performance by enlarging the existing investment opportunity set.

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