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Wenting JIAO

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devant le jury composé de :

Khalid EL BADRAOUI
Professeur Habilité à Diriger des Recherches, Université Ibn Zohr (Maroc) / *rapporteur*

Franck MORAUX
Professeur à l'Université de Rennes 1 / membre

Hélène RAINELLI-WEISS
Professeur à l'Université de Strasbourg / *rapporteur*

Jean-Jacques LILTI
Professeur à l'Université de Rennes 1 / *directeur de thèse*

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Abbreviations

3M T-Bill Rate: Three-Month Treasury Bill Rate

ANNA: Artificial Nerve Network Analysis

B/M: Book-to-market equity

B/P: Book-to-price

BS: Black-Scholes

BSM: Black-Scholes and Merton

CDS: Credit default swaps

Chinese A-share: CNAS

Cross-sectional regression: CSR

CSRC: China Securities Regulatory Commission

DD: Distance-to-default

DEF: Default spread

DIV: Dividend yield

DLI: Default likelihood indicator

DP: Default (distress) probability

DR: Distress (default) risk

DRF: Distress risk factor

E/P: Earning-to-price

EDF: Expected default frequency

FF: Fama-French

FF3F Model: Fama-French Three-Factor Model

FF5F Model: Fama-French Five-Factor Model

FM: Fama-MacBeth

GBM: Geometric Brownian Motion

GEB: Growth Enterprise Board

GDP: Gross Domestic Product

GNP: Gross National Product

ICC: Implied cost of capital

IDEF: Innovations of default spread

IDIV: Innovations of dividend yield

IHML: Innovations of HML

Inv: Investment

IRF: Innovations of one-month deposit rate

ISMB: Innovations of SMB

ITERM: Innovations of term spread

LTD: Long-term debts

MDA: Multiple discriminant analysis

OP: Operating profitability

PT: Particular transfer

RF: Risk-free Rate (one-month deposit rate)

RMB: RenMinBi (Chinese ‘yuan’)

SBPD: Size-B/P-DLI

SBPO: Size-B/P-O-score

SDF: Stochastic Discount Factor

SH: Shanken

SHASHR Index: Shanghai Stock Exchange A-Share Index

SME: Small Medium Enterprise Board

SSE: Shanghai Stock Exchange

ST: Special treatment

STD: Short-term debts

SV: Survival rate

SZASHR Index: Shenzhen Stock Exchange A-Share Index

SZSE: Shenzhen Stock Exchange

t-stats: t-statistics

TERM: Term spread

Time-series regression: TSR

VAR: Vector-autoregressive

Résumé de la thèse en français

Introduction générale

Les modèles de facteurs ont été les modèles dominants dans le domaine de prix de l'actif depuis des décennies depuis l'apparition du 'Capital Asset Pricing Model' (CAPM) de Sharpe (1964), Lintner (1965) et Black (1972). Le CAPM d'origine peut être considéré comme le modèle de facteur à indice unique et facile à effectué et à interpréter; cependant, il est critiqué pour ses hypothèses et le manque du pouvoir explicatif des anomalies du marché boursier. D'innombrables chercheurs se sont consacrés à développer un modèle qui remédie aux défauts de CAPM. Les adversaires de CAPM qui voient son manquement du pouvoir explicatif affirment qu'il doit y avoir d'autres facteurs en dehors de la rentabilité excédentaires du marché qui dérivent la rentabilité de l'actif. Les modèles d'évaluation des actifs qui ont plus d'un facteur sont appelés modèles multifactoriels.

L'un des modèles multifactoriels fondamentaux est 'Arbitrage Pricing Theory' (APT) introduite par (Ross, 1976). Dans cette théorie, la plupart des hypothèses sous-jacentes au CAPM sont assouplies. L'APT suppose qu'il y a n facteurs qui causer la rentabilité de l'actif s'écartent systématiquement de leurs valeurs espérées, mais la théorie ne précise pas à quel point le nombre n, ni identifie les facteurs.

Fama et French (1993) déduit un modèle empirique purement à trois facteurs qui inclut un facteur lié à la taille de l'entreprise (SMB) et un facteur lié au ratio book-to-market (HML) de l'entreprise, en plus de bêta du marché de CAPM, c'est le Modèle à Trois Facteurs de Fama-French (FF3F) célèbre. Ils fournissent de fortes preuves empiriques que le modèle à trois facteurs capture la plupart des variations la rentabilité de l'actif en coupe dans le marché d'action des États-Unis. En outre, la source ouverte sur le site de Kenneth R. French facilite également les recherches. Il est également intéressant de noter que le modèle de Fama-French (FF) est l'une des principales raisons pour lesquelles le Professeur Fama reçoit le Prix Nobel de Economie 2013. Depuis l'apparition du Modèle FF3F, une énorme quantité de travail a été effectué selon le Modèle FF3F, par exemple, chercher de nouveaux facteurs ou examiner comment le Modèle FF3F fait sur marchés des actions différents partout dans le monde. Actuellement, plus de chercheurs se tournent vers la recherche de la fondation économique en arrière les facteurs ou les applications en pratique.

Les modèles de facteurs, en particulier le CAPM et le Modèle FF3F, occupent pas seulement un rôle pivot dans le développement de la théorie d'évaluation des actifs, mais contribuent également à la pratique du marché et à l'analyse des investissements. Ils sont largement utilisés par les gestionnaires de portefeuille, les investisseurs institutionnels, les gestionnaires financiers et les investisseurs individuels, à tel que la prédiction de la rentabilité d'actif, la sélection de titres, la construction de portefeuille et contrôle du risque, quantifier l'exposition au risque d'un portefeuille par rapport à un indice de référence, mesurer la performance, et l'évaluation du gestionnaire de portefeuille.

L'utilisation des modèles de facteurs comme une base pour les recherches est devenue standard dans la littérature financière. La preuve que les facteurs FF sont largement utilisés peut être trouvée dans les journaux principaux dans le domaine financier, 'The Journal of Finance' et 'Journal of Financial Economics'. Ces deux journaux de premier ordre sont classés dans les revues A-étoile (l'évaluation le plus élevée). Ils sont habituellement classés dans les deux ou trois revues financières les plus importantes du monde. Plus récemment, Fama et French (2015a) proposent un modèle à cinq facteurs visant à capturer la taille, la valeur, la rentabilité et l'investissement dans le rendement d'action sur le marché boursier américain dans le 'Journal of Financial Economics'; et fournir le test international du modèle à cinq facteurs (Fama et French, 2017).

En outre, plus preuves empiriques ou pratiques que les modèles de facteurs sont largement utilisés peuvent être trouvés dans 'The Journal of Portfolio Management' (JPM), qui est une des revues qui propose des recherches en pointe sur l'allocation d'actifs, la mesure de la performance, les tendances du marché, la gestion des risques, l'optimisation de portefeuille, etc. Les articles publiés par JPM proviennent pas seulement des chercheurs les plus renommés, mais aussi des praticiens renommés. En particulier, JPM a publié un numéro spécial de 2017 pour célébrer ses 40 ans, qui contient les recherches les plus récentes relatives aux facteurs de risque ou aux modèles des facteurs. Trois articles (Bass et al., 2017; Cocoma et al., 2017; et Bender et Samanta, 2017) prend l'objet d'allocation de portefeuille fondée sur des facteurs. Quatre articles sont basés sur l'investissement fondé sur les facteurs. Deux autres articles sont sur les méthodologies pour construire les portefeuilles de facteurs: Amenc et al. (2017) fournissent deux méthodes de construction de portefeuilles multifactoriels, tandis que Liu (2017) propose un portefeuille de quintile avec un nouveau cadre de construction de facteurs.

Nous énumérons ci-dessous plusieurs applications de modèles de facteurs en pratique:

- Gestion de portefeuille

Le pouvoir d'un modèle multi-facteurs est que compte tenu des facteurs des risques et des sensibilités aux facteurs des risques, le profil d'exposition au risque d'un portefeuille peut être quantifié et contrôlé. Un gestionnaire de portefeuille peut également analyser son risque actuel et comprendre la taille et l'emplacement de ses paris. D'autre part, les modèles de facteurs peuvent être utilisés pour décomposer le risque du portefeuille en fonction de l'exposition aux facteurs communs, et pour évaluer la part de la rentabilité d'un portefeuille attribuable à chaque exposition aux facteurs communs. En utilisant un modèle de multifactoriel et un modèle d'optimisation, on peut construire un portefeuille présentant le minimum de risque actif par rapport à son indice de référence pour un nombre donné d'actifs détenus. Similairement, un gestionnaire de portefeuille peut construire un portefeuille qui s'incline vers un facteur spécifié et ce portefeuille n'a aucune exposition active matérielle à aucun autre facteur. En plus, les modèles multifactoriel de risque permettent à un gestionnaire et à un client d'évaluer les performances potentielles d'un portefeuille ou d'une stratégie de négociation par rapport à un indice de référence.

- Estimation de rentabilité exigé et évaluation de l'équité

Les modèles de facteurs sont largement utilisés pour estimer le taux de rentabilité du capital exigé, compte tenu du risque pertinent. Si les investisseurs s'attendent à une rentabilité d'action particulier supérieur à une rentabilité exigé, l'action est sous-évalué; en revanche, si la rentabilité espérée est inférieur au taux de rentabilité exigé, l'action est surévalué. Le taux de rentabilité exigé est une composante dans plusieurs des métriques et des calculs utilisés dans finance d'entreprise et évaluation de l'équité.

L'évaluation de l'équité est une partie centrale dans des nombreuses activités, telles que la sélection des titres, l'analyse des actions, en déduisant des attentes du marché, l'évaluation des événements d'entreprise et l'évaluation des entreprises privées. Les gestionnaires des actifs effectuent les évaluations parce que leur objectif principal est identifier les titres mal cotés (sous-évalués ou surévalués). Les banques d'investissement qui jouent un rôle intermédiaire dans l'événements d'entreprise, par exemple dans les fusions et acquisitions, procèdent également à l'évaluation de l'entreprise cible. Un analyste d'action évalue les actions qu'elle (ou il) suite (suit) pour donner des recommandations (acheter, tenir, vendre). Les analystes ou les chercheurs utilisent souvent des modèles d'évaluation pour extraire les attentes du marché. Par exemple, un analyste peut inscrire le prix du marché et le taux d'intérêt, le dividende et d'autres facteurs dans un modèle d'évaluation de l'équité afin de déterminer quel taux de croissance le marché implique.

- La pratique de la finance d'entreprise et le coût de l'estimation de l'équité

Le coût du capital est la rentabilité exigé nécessaire pour réaliser un projet de budgétisation en capital. Il comprend le coût de la dette et le coût de l'équité. Les modèles de facteurs sont généralement utilisés pour mesurer le coût de l'équité (COE). COE est la rentabilité que les actionnaires ont besoin pour leur investissement dans une entreprise. Le COE d'une entreprise représente la compensation que la demande du marché en échange de posséder l'actif et portant le risque de propriété. Les actionnaires s'attendent à obtenir une certain rentabilité sur leurs participations dans une entreprise, le taux de rentabilité exigé par les actionnaires est un coût au point de vue de l'entreprise. Le coût de l'équité est essentiellement ce qu'il coûte à l'entreprise de maintenir un prix d'action qui est théoriquement satisfaisant pour les investisseurs. Sur cette base, la méthode le plus couramment acceptée pour calculer le coût de l'équité provient du CAPM et le Modèle FF3F.

- Investissement à base de facteur

Investissement à base de facteur est devenu une partie largement discutée du canon d'investissement d'aujourd'hui. Les chercheurs d'investissement utilisent des modèles multifactoriels des risques pour exécuter des back-tests contrôlés sur les stratégies d'investissement futures. Pour cela, leurs besoins sont semblables à ceux des gestionnaires de portefeuille. Ils doivent mettre en œuvre des stratégies optimales sur les données historiques et comprendre la performance ultérieure de ces stratégies. Les chercheurs peuvent utiliser des back-tests pour améliorer leurs stratégies. Ils peuvent également utiliser l'analyse de performance et la caractérisation des risques de portefeuille pour améliorer leur compréhension des paris qu'ils testent. La preuve que l'investissement factoriel est en vogue peut également être trouvée dans le dernier numéro spécial (2017) de Journal of Portfolio Management. Deux articles (Dimson et al., 2017 et Kim et al., 2017) se concentrer sur l'investissement basé sur les facteurs, et deux articles (Podkaminer, 2017 et Alford et Rakhlin, 2017) sur la bêta intelligente qui est une stratégie d'investissement factorielle populaire actuellement. Par exemple, MSCI a créé une famille d'indices de facteurs (index bêta intelligents) qui permettent d'accéder à six facteurs solides: valeur, taille faible, volatilité faible, rendement élevé, qualité et élan.

Une débauche de recherches et l'utilisation pratique largement des modèles de facteurs sont les deux motivations de cette thèse. En plus, la croissance d'économique significative en Chine au cours des dernières décennies a été universellement reconnue, la Chine a maintenant la deuxième grande économie au monde, et elle est le plus grand pays en développement. Le marché boursier chinois, créé en 1990, est un représentant des marchés émergents avec une histoire relativement courte. Son développement ainsi que son immaturité ont attiré l'attention des chercheurs, et ont apportés la question si les modèles d'évaluation des actifs tels que le modèle de FF s'appliquent également à ses marchés domestiques. Par conséquent, la popularité des modèles de facteurs et le marché boursier émergent stimulent l'intention pour l'étude des modèles factoriels sur le marché boursier chinois. On peut dire que ceci encore une autre étude des modèles de facteurs sur la base du Modèle FF3F, mais ce que nous voulons souligner, c'est que le modèle FF3F est devenu la pierre angulaire des études des facteurs, la recherche sur les modèles de facteurs a été un sujet de recherche chaud pendant des décennies, et il continuera d'être un thème clé du domaine d'évaluation des actifs à l'avenir.

Le travail présenté dans cette thèse contient trois chapitres, explorant principalement les facteurs de risque sur le marché boursier chinois sur la base du Modèle FF3F. Le succès du Modèle FF3F sur le marché boursier des États-Unis stimule les études sur l'applicabilité dans d'autres marchés développés ou émergents partout dans le monde, l'applicabilité du Modèle FF3F sur le marché boursier chinois a également été un sujet d'actualité depuis des années. Cette thèse commence par un nouveau test du Modèle FF3F à l'aide des données du marché boursier chinois A-share, afin de répondre à la question si le Modèle FF3F s'applique au marché boursier chinois A-share. Les travaux suivants se déroulent à partir de Modèle FF3F.

Le chapitre 1 ré-enquête sur le Modèle FF3F et explore le dernier Modèle à Cinq Facteurs de Fama-French (FF5F) sur le marché boursier chinois A-share, vise à examiner l'applicabilité des deux modèles en Chine. En outre, nous comparons les résultats de régression des deux modèles pour vérifier si Modèle FF5F fonctionne mieux que le Modèle FF3F pour capturer la variation des rentabilités des actions. Il est important de noter que nous prenons en compte plusieurs caractéristiques particulières du marché boursier chinois qui ne sont pas négligeables pour bénéficier de résultats de recherche plus fiables.

Pour mettre en œuvre l'enquête, nous construisons les cinq facteurs: rentabilités excédentaire du marché, facteur de taille SMB, facteur de valeur HML, facteur de rentabilité RMW et facteur d'investissement CMA en utilisant des données du marché boursier chinois A-share. L'approche à deux étapes de Fama-MacBeth (1973) est appliqué pour les régressions séries chronologiques et les régressions transversales. Étant donné que l'approche à deux étapes de Fama-MacBeth (FM ci-dessous) a causé le problème d'erreurs sur les variables (EIV), la procédure de correction proposée par Shanken (1992) est appliquée.

Bien que la grande réussite du modèle de facteur FF, c'est aussi l'un des modèles d' évaluation des actifs qui sont les plus controversés, principalement pour ses considérations purement empiriques et le manque de fondements théoriques. Le succès du Modèle FF3F stimule la poursuite des bases économiques des facteurs FF. Au chapitre 2, nous procédons à la recherche conformément à l'une des explications dominantes, basée sur des opportunités d'investissement variant dans le temps dans le cadre de l'ICAPM. Nous examinons si les facteurs FF sont proxys des innovations de variables d'état sélectionnées qui décrivent les opportunités d'investissement futures sur le marché boursier chinois A-share. Nous choisissons quatre variables économiques selon Petkova (2006): rendement en dividende agrégée, taux de T-bonds en un mois, l'écart de terme et l'écart de défaut, afin de modéliser deux aspects de l'opportunité d'investissement set- la courbe de rendement et la distribution conditionnelle des rentabilités des actifs.

Pour extraire les termes de l'innovation, le processus de Vecteur Autoregressif (VAR) a été utilisé. Et comme Campbell (1996) souligne que'il est difficile d'interpréter les résultats d'estimation pour un modèle de facteur VAR, sauf si les facteurs soient orthogonalisés et mis à l'échelle d'une certaine manière", nous orthogonalisons les innovations des variables d'état sur la rentabilité excédentaire du marché, qui est le premier élément du vecteur dans le processus VAR. L'approche à deux étapes de Fama-MacBeth est ensuite mise en place pour les régressions séries chronologiques et les régressions transversales, et les résultats de la régression transversale sont ajustés pour le problème de l'EIV.

Dans le chapitre 3, nous choisissons le facteur de risque détresse comme facteur augmenté du Modèle FF3F original parmi les facteurs de risque qui ont été découverts. Étant donné que le risque détresse de l'entreprise est un indicateur important de la performance d'une entreprise, et est également l'une des caractéristiques les plus concernées par les investisseurs et les entreprises. De plus, le risque de détresse financière a été prouvé lié aux rentabilités des actions étroitement et le point de vue de l'effet de la valeur est considéré comme l'effet du risque de détresse proposé par la littérature séries chronologique.

L'objectif principal est de tester si les facteurs FF sont des procurations pour le risque de détresse sur le marché boursier chinois pendant la période de juillet 2005 à mai 2015. Sinon, si le modèle à quatre facteurs augmenté explique la rentabilité d'action mieux que le Modèle FF3F. En particulier, nous appliquons le modèle à base de comptabilité (O-score d'Ohlson) et le modèle de marché (DLI des Vassalou et Xing) pour mesurer la détresse financière, afin d'identifier si les méthodes différentes qui prédisent du risque de détresse sont importantes pour les résultats empiriques. En outre, la relation entre la rentabilité d'action et le risque de détresse, et si l'effet de taille et l'effet de valeur sont liés au risque de détresse ont également été examinés sur le marché boursier chinois.

Chapitre 1

Modèle à Cinq-Facteurs de Fama-French versus Modèle à Trois-Facteurs de Fama-French en Chine

Contexte et objectif

Fama et French (1993) proposent le Modèle FF3F et démontrent que le facteur de taille et le facteur de valeur ont effectué réussi à expliquer les rentabilités des actions en plus du bêta du marché. Dernier, Fama et French (2015a) proposent un modèle à cinq facteurs incluant le facteur rentabilité et le facteur d'investissement en plus des trois facteurs original de FF, et ce modèle se comportent mieux que le Modèle FF3F.

Le Modèle FF3F et le Modèle FF5F sont:

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t} \tag{1}$$

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{i,t} \tag{2}$$

Il est évident que le modèle à cinq facteurs comporte deux autres facteurs que le modèle à trois facteurs, RMW et CMA. RMW est le facteur lié à la rentabilité de l'entreprise, ce qui correspond à la différence de rentabilité entre les portefeuilles qui ont les rentabilités robustes et les rentabilité faible. Le CMA est liée à l'investissement, lequel est la différence de rentabilité entre les portefeuilles qui ont les investissements conservatifs et les portefeuilles qui ont les investissements agressifs.

Ce chapitre ré-examine l'applicabilité du Modèle FF3F en construisant des facteurs FF sur le marché boursier chinois A-share (séries chronologique et transversales), compte tenu de plusieurs caractéristiques spéciales du marché boursier chinois. De plus, ce chapitre étudie également le dernier Modèle FF5F en utilisant les données du marché boursier chinois, afin d'examiner si les facteurs de rentabilité et d'investissement ont un pouvoir explicatif supplémentaire. En outre, nous comparons deux modèles pour voir si le Modèle FF5F fonctionne mieux que le Modèle FF3F sur le marché boursier chinois A-share. Les comparaisons des résultats empiriques entre le marché boursier chinois et le marché boursier américain sont également exécutés.

Caractéristiques spécials du marché boursier chinois

Les littératures empiriques suggèrent que le marché chinois présente des caractéristiques spécials, et il est inévitable de considérer ces caractéristiques spécials si les chercheurs veulent avoir des résultats plus précis en Chine. Dans notre étude, nous résumons trois caractéristiques principales qui sont également les plus fréquemment employées par les littératures: (1) utiliser des actions négociables, pas toutes les actions (y compris les actions négociables et non-négociables) pour pondérer la rentabilité d'action en valeur, (2) inclure les entreprises de 'Petit Moyen Enterprise Planche' et 'Croissance Enterprise Planche' pour déterminer les points de ruptures pour le facteur de taille, et (3) calculer le ratio book-to-price (B/P) au lieu du ratio book-to-market (B/M) puisque la segmentation du marché boursier chinois .

Données et méthodologie

Nous incluons toutes les entreprises sur le marché boursier chinois A-share (marché boursier A-share de Shanghai et marché boursier A-share de Shenzhen), à l'exclusion des entreprises financières et des entreprises ayant des valeurs des B/P négatives; en plus, une entreprise est éliminée si les informations pertinentes manquent dans un mois ou une période donné. La période de recherche pour le Modèle FF3F est de juillet 2004 à mai 2015 (131 mois), et le Modèle FF5F est de juillet 2010 à mai 2015 (59 mois).

L'approche en deux étapes de Fama-MacBeth (FM) est appliquée pour les régressions, la première étape est la série chronologique en utilisant l'OLS. La deuxième étape est la régression transversale telle qu'indiquée dans l'équation (1), où ils utilisent les bêtas estimées obtenues de la première étape des régressions chronologiques, comme les variables indépendantes dans les régressions transversales. Et réglez les rentabilités des mêmes portefeuilles (que dans la première étape) sur ces bêtas estimées pour une période de temps fixe pour déterminer la prime de risque pour chaque facteur.

$$R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB} \hat{s}_i + \gamma_{HML} \hat{h}_i + \varepsilon_{i,t} \quad (3)$$

Étant donné que l'approche en deux étapes de FM cause le problème d'erreurs sur les variables (EIV) classiques, la procédure de correction proposée par Shanken (1992) est ensuite appliquée aux écarts types des estimateurs de régression transversale.

Construction de portefeuilles et de facteurs

À la fin de juin de chaque année *t*, tous les actions sont triés en deux groupes de taille, Petit et Grand, le point de rupture est la médiane de la capitalisation boursière totale. Nous classons par B/P au lieu du B/M à la fin de chaque décembre de l'année *t-1* en trois groupes: Bas, Moyen et Haut cela dépend des points de rupture des 30e et 70e percentiles de A-share. Enfin, l'intersection de ces six groupes fait les six portefeuilles, qui restent les mêmes de juillet de l'année *t* à juin de l'année *t+1*, et les portefeuilles sont réformés en juillet de l'année *t+1*.

	La médiane de la capitalisation boursière	
	Petit Bas	Grand Bas
30e percentil B/P		
	Petit Moyen	Grand Moyen
70e percentil B/P		
	Petit Haut	Grand Haut

Les facteurs SMB et HML est construit comme suit:

$$SMB = \frac{1}{3}(\,Petit\ Bas + Petit\ Moyen + Petit\ Haut) \\ - \frac{1}{3}(\,Grand\ Bas + Grand\ Moyen + Grand\ Haut\,) \quad (4)$$

$$HML = \frac{1}{2}(\,Petit\ Haut + Grand\ Haut\,) - \frac{1}{2}(\,Petit\ Bas + Grand\ Bas\,) \quad (5)$$

Similairement, la construction de portefeuilles sur la rentabilité opérationnelle (OP) et l'investissement (Inv) est similaire en celle des portefeuilles sur le ratio B/P. À la fin de chaque mois de juin, les entreprises sont triées en trois portefeuilles OP basé sur des points ruptures des 30e et 70e percentiles de l'OP, et les trois portefeuilles d'investissement sont formés à l'aide de points rupture: les 30e et 70e percentiles d'Inv. Ensuite, les facteurs RMW et CMA sont les suivants:

$$RMW = \frac{1}{2}(\,Petit\ Robuste + Grand\ Robuste) - \frac{1}{2}(\,Petit\ Faible + Grand\ Faible\,) \quad (6)$$

$$CMA = \frac{1}{2}(\,Petit\ Conservatif + Grand\ Conservatif) \\ - \frac{1}{2}(\,Petit\ Agressif + Grand\ Agressif\,) \quad (7)$$

Nous construisons trois séries de portefeuilles: six portefeuilles Taille-B/P pondérées en valeurs, six portefeuilles Taille-OP pondérées en valeurs et six portefeuilles Taille-Inv pondérées en valeurs, en tant que variables dépendantes pour effectuer les régressions.

Résultats et conclusions

Le Modèle FF3F peut expliquer la majorité des variations chronologiques des rentabilités des actions, compte tenu des caractéristiques spécials du marché boursier chinois. Au cours des périodes de juillet 2004 à mai 2015, il existe une prime de taille positif dans la rentabilité d'actions sur le marché boursier chinois A-share, toutefois, nous constatons le manque de prime de valeur. Le bêta du marché est capable d'expliquer la variation transversale des rentabilités moyens pour les 25 portefeuilles pondérés en valeur (avec des t-statistiques SH ajustés négatifs).

Pour tous les trois séries de portefeuilles que nous avons construits dans la recherche du Modèle FF5F, il existe un effet de taille; tandis qu'il existe un effet de valeur dans les portefeuilles Taille-B/P, l'effet de rentabilité dans les portefeuilles Taille-OP et l'effet d'investissement dans les portefeuilles Taille-Inv. Les coefficients sur RMW ne sont significatives que dans la serie des portefeuilles qui formés à partir de taille et OP. En ce qui concerne le facteur CMA, les coefficients significatives sont concentrées dans les groupes OP ou Inv extrêmes, tels que le groupe OP faible, le groupe OP robuste, les groupes Inv agressifs et conservatif. Cependant, pour les portefeuilles Taille-B/P, les coefficients significatifs de CMA sont relativement dispersifs.

Nous comparons la performance entre le Modèle FF3F et le Modèle FF5F au cours de la période de recherche, si le Modèle FF5F fonctionne mieux que le Modèle FF3F sur le marché boursier chinois A-share n'est pas très clair. Le pouvoir explicatif du Modèle FF5F est différent parmi les séries de portefeuilles différents. Par rapport au Modèle FF3F, la présence de facteurs de rentabilité et d'investissement ne capturer pas plus de variations des rendabilités des actions espérés que le modèle à trois facteurs, à l'exception des six portefeuilles pondérées en valeurs qui formés à partir de la taille et de la rentabilité opérationnelle, bien que l'amélioration soit limitée.

Nous comparons également performances des Modèles FF entre le marché boursier chinois et le marché boursier américain. Les résultats révèlent que le Modèle FF3F et le Modèle FF5F expliquent la variation de séries chronologiques des rendabilités meilleure sur le marché boursier américain par rapport au marché boursier chinois. En ce qui concerne les deux facteurs supplémentaires, le facteur de rentabilité RMW et le facteur d'investissement CMA, sont capables de capturer partiellement les variations de séries chronologiques des rendabilités des trois séries portefeuilles sur le marché boursier américain, alors que sur le marché boursier chinois, le facteur de rentabilité semble être un facteur explicatif seulement pour les six portefeuilles Taille-OP.

Chapitre 2

Fama-French Facteurs et Innovations des Variables d'état sur le Marché Boursier Chinois

Objectif

Le Modèle FF3F a réalisé un énorme succès empirique depuis son apparition, donc il est considéré comme l'un des modèles les plus controversés d'évaluation actif. Cependant, les facteurs sont construits empiriquement .donc ils manquent de fondements théoriques. En particulier, leurs liens économiques avec le risque systématique ne sont pas clairs. Par conséquent, la performance impressionnante du Modèle FF3F a suscité des recherches nombreuses qui tentent de fournir une interprétation économique claire des facteurs HML et SMB.

Les liens économiques sous-jacents des facteurs FF sont plutôt controversés. Parmi des nombreuses des explications concurrentes pour le succès du Modèle FF3F, suivant que Petkova (2006), dans ce chapitre, nous concentrons sur celui basé sur des opportunités des investissements qui variant dans le temps et dans le contexte d’Intertemporal Capital Asset Pricing Model (ICAPM ci-après) de Merton (1973a).

Dans ce chapitre, nous examinons si les innovations des quatre variables d'état, rendement du dividende agrégée, taux de T-bonds en un mois, l'écart de terme et l'écart de défaut, sont capables de capturer les rentabilités excédentaires des actions dans les séries chronologiques et séries transversales. Nous examinons également si FF Facteurs SMB et HML sont les proxys pour les innovations de variables d'état sélectionnées, qui décrivent les opportunités d'investissement futures sur le marché boursier chinois A-share.

Données et méthodologie

Le même sérier des variables d'état que Petkova (2006) est choisi en plus des facteurs FF dans notre test empirique: rendement de dividende agrégée (DIV), l'écart de terme (TERM), l'écart de défaut (DEF) et taux de T-bonds en un mois (RF), qui sont parmi les variables économiques qui sont utilisées les plus communes dans les littératures. La période de recherche est de décembre 2006 à mai 2015 (102 mois).

Selon ICAPM, seul le composant inattendu de la variable d'état devrait commander une prime de risque. Le composant inattendu est normalement appelé innovations. Au lieu d'utiliser directement les variables d'état pour l'implémentation empirique de l'ICAPM, Campbell (1996) suggère d'utiliser des innovations dans telles variables d'état pour prévoir les changements dans le sérier des opportunités d'investissement futures. Pour dériver les termes de l'innovation, nous appliquons la méthode vecteur autorégressif (VAR).

$$\begin{Bmatrix} R_{m,t} \\ DIV_t \\ TERM_t \\ DEF_t \\ RF_t \\ SMB_t \\ HML_t \end{Bmatrix} = A \begin{Bmatrix} R_{m,t-1} \\ DIV_{t-1} \\ TERM_{t-1} \\ DEF_{t-1} \\ RF_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \end{Bmatrix} + u_t \tag{8}$$

Où ‘A’ est une matrice 7 × 7, et représente un vecteur d'innovations de 7 × 1 pour chaque élément. Il y a six innovations correspondant au rendement du dividende, au taux de T-bonds en un mois, à l'écart de terme (TERM), à l’écart de défaut, au SMB et au HML, qui sont extraits de et designés IDIV, IRF, ITERM, IDEF, ISMB et IHML.

Les innovations peuvent être exprimées dans le cadre de l’ICAPM:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,m}\left(R_{M,t} - R_{f,t}\right) + \sum_{1}^{K} \beta_{i,\mu^k}\left(\mu_t^k\right) + e_{i,t} \tag{9}$$

où, μ_t^k est l’innovation de l’état variable k au temps t.

Ensuite, les innovations des variables d'état sont séparément orthogonalisées au facteur du marché. Précisément, l'innovation de la rentabilité excédentaire du marché reste inchangée, l'innovation du rendement de dividende IDIV est orthogonalisé à la rentabilité excédentaire du marché. De même, IRF est orthogonalisée au facteur du marché. Les autres innovations des variables d'état ITERM, IDEF, ISMB et IHML sont traitées par la même manière.

Puis l'approche à deux étapes de Fama-MacBeth est implémentée pour effectuer les régressions pour cinq modèles comparatifs, et la correction de Shanken est également effectuée pour ajuster le problème EIV dans les régressions transversales.

Cinq modèles comparatifs

Modèle 1

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \beta_{i,ISMB} ISMB + \beta_{i,IHML} IHML + e_{i,t} \end{aligned} \tag{10}$$

Modèle 2

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \beta_{i,SMB} SMB + \beta_{i,HML} HML + e_{i,t} \end{aligned} \tag{11}$$

Modèle 3

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + e_{i,t} \end{aligned} \tag{12}$$

Modèle 4

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,ISMB} ISMB + \beta_{i,IHML} IHML + e_{i,t} \tag{13}$$

Modèle 5

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,SMB} SMB + \beta_{i,HML} HML + e_{i,t} \tag{14}$$

Le modèle 1 représente les régressions chronologique sur la rentabilité excédentaire du marché, les innovations des variables d'état et les innovations des facteurs FF SMB et HML (ISMB et IHML). Le modèle 2 représente les régressions chronologiques sur la rentabilité excédentaire du marché, les innovations des variables d'état et les facteurs FF initiaux SMB et HML. Les variables indépendantes dans le modèle 3 sont les rentabilités excédentaire du marché et quatre innovations des variables d'état. Dans le modèle 4, les variables indépendantes sont les rentabilités excédentaire du marché et les innovations de SMB et HML. Le modèle 5 n'est que le Modèle FF3F original.

Nous réalisons les séries chronologiques suivant les cinq modèles ci-dessus et réalisons également les régressions transversales correspondant aux cinq modèles comparatifs.

Résultats et conclusions

Nous pouvons conclure que les facteurs FF (ou les innovations des facteurs FF) expliquent bien la variation des séries chronologiques des rentabilités attendus des actions, avec ou sans les innovations des variables d'état dans le modèle. Lorsque les quatre innovations des variables d'état sont respectivement régressées, seulement IDIV a un pouvoir explicatif pour la rentabilité moyenne; en présence de facteurs FF (ou des innovations des facteurs FF), IDIV perd sa capacité à capturer les variations des rentabilités chronologiques attendus.

La présence des quatre innovations de variables d'état qui prévoient des opportunités d'investissement futures ne expulse pas les facteurs FF. L'information contenue dans l'innovation des rendements de dividende IDIV semble totalement capturée par la combinaison du marché bêta et le SMB (ou ISMB). Bien que le modèle comporte à la fois des facteurs FF et des innovations de variables d'état (comme les facteurs de risque) effectue légèrement meilleurs que le Modèle FF3F original (compte tenu de R-carré moyenné ajusté), les FF facteurs ont pu jouer un rôle limité en capturant d'opportunités d'investissement alternatives représentées par les innovations des variables d'état.

Chapitre 3

Facteur de Risque de Détresse et Rentabilités des Actions sur le Marché Boursier Chinois

Objectif

L'étude du chapitre 2 est basée sur l'une des trois théories spécifiques les plus discutées: l'exposition aux changements dans les variables économiques dans le contexte de l'ICAPM (les deux autres théories spécifiques sont le risque de détresse et l'exposition asymétrique aux conditions économiques). Les résultats démontrent que les facteurs FF ne représenter pas les innovations des quatre variables sélectionnées sur le marché boursier chinois A-share pendant la période de décembre 2006 à mai 2015. Une autre explication théorique, le risque de détresse, est étudié dans ce chapitre. Puisque une explication de la performance des rentabilité persistants des hauts B/M actions est le risque de détresse financière.

Ce chapitre étudie la relation entre les rentabilites des actions et le risque de détresse, et aussi examine si l'effet de taille et l'effet de valeur sont liés au risque de détresse sur le marché boursier chinois A-share. De plus, nous explorons un modèle à quatre facteurs en ajoutant un facteur de risque de détresse en plus des trois facteurs FF afin d'examiner si facteurs FF sont des proxys de facteurs de risque de détresse. Nous examinons si différentes méthodes de construction des facteurs entraînent des résultats différents.

La mesure de risque de détresse financière

Parmi les méthodes de prévision du risque de détresse, l'utilisation de ratios comptables et d'informations sur le marché sont deux classifications dominantes. Les modèles qui utilisent des ratios comptables pour estimer le risque de détresse s'appellent les modèles basés sur la comptabilité, par exemple, le 'Z-score' de Altman (1968) et le 'O-score' de Ohlson (1980). Les modèles qui utilisent l'information du marché pour estimer le risque de détresse sont les modèles basés sur le marché, représentés par le modèle de 'option-pricing' de Merton (1974) et le modèle KMV de Moody.

Pour mesurer le risque de détresse financière, deux modèles de prédiction dominants sont mis en place sur le marché boursier chinois: O-score de Ohlson (1980) (modèle basé sur la comptabilité)

$$\begin{aligned} O = & -1.32 - 0.407\log(SIZE) + 6.03(TLTA) - 1.43(WCTA) + 0.076(CLCA) \\ & -1.72(OENEG) - 2.37(NITA) - 1.83(FUTL) + 0.285(INTWO) - 0.521(CHIN) \end{aligned} \quad (15)$$

et le modèle de de 'option-pricing' de Merton (1974) (modèle basé sur le marché)

$$DP_t = N\left(-\frac{ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}} \right) \quad (16)$$

Vassalou et Xing (2004) soulignent que leur probabilité défaut (DP) estimée en utilisant du modèle de Merton n'est pas le DP réel, au lieu de cela, le DP calculé basé sur la distribution empirique du modèle KMV de Moody est le DP actuel. Ainsi, ils appellent leur mesure de DP comme l'indicateur de probabilité par défaut (DLI).

Afin d'étudier si les trois facteurs FF sont des proxys pour le risque de détresse, un modèle augmenté à quatre facteurs, qui comprend le facteur de marché (bêta du marché), le facteur de taille (SMB), le facteur de valeur (HML) et le facteur de risque de détresse (DRF), est examiné:

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + d_i DRF + \varphi_{i,t} \tag{17}$$

Si toutes les informations dans SMB et HML sont liées au risque de détresse financière, il est probable de trouver que SMB et HML perdent toute leur capacité à expliquer les rentabilités des équités. en présence de DRF.

Données et méthodologie

Dans ce chapitre, les données de recherche proviennent d'une période de juillet 2005 à mai 2015 (119 mois). Dans la recherche des deux méthodes, les entreprises financières, dont la structure capitale se distingue de celle des ordinaires, est exclu. Les entreprises ayant un ratio B/P négatif sont également retiré de l'échantillon. Puisque cet recherche se concentre sur les entreprises saines, les entreprises qui ont qualifié 'Traitement spécial' et 'Transfert particulier' en Chine sont également hors de notre considération.

Pour procéder la recherche et pour effectuer la comparaison, tout d'abord,la probabilité par défaut est calculée en appliquant la formule de O-score d'Ohlson (mesure basée sur la comptabilité) et une procédure itérative complexe est utilisé pour résoudre le modèle de 'option-pricing' afin de calculer le DLI (mesure basée sur le marché). Ces probabilités par défaut sont ensuite utilisées comme un critère principal pour la distinction du risque de détresse des entreprises.

Les proxys du risque de détresse que nous utilisons sont les DP calculés par O-score et DLI. À la fin de chaque mois de juin de l'année *t*, nous classons les actions selon leur O-score (ou DLI) de fin d'année *t-1* en trois groupes, désignés comme O1, O2 et O3 (ou DLI1, DLI2, DLI3) de bas à haut des probabilités défauts. Les points des reptures sont 30% et 70% des percentiles du O-score (ou DLI) d'échantillonnage. Les portefeuilles restent immuables de juillet de l'année *t* à juin de l'année *t+1*, et il sont réformés à la fin de juin de l'année *t+1*. Les données sont traité comme ça pour toute la période de recherche. Le portefeuille imitant DRF est le facteur de risque de détresse, qui mesure la différence de rentabilité entre le portefeuille DP haut (O3 ou DLI3) et le portefeuille DP bas (O1 ou DLI1).

Les comparaisons sont effectuées entre les résultats obtenus à partir des deux modèles différents (le modèle basé sur la comptabilité et le modèle basé sur le marché). Ensuite, de la même manière que les chapitres précédents, l'approche à deux étapes de Fama-MacBeth et la méthode ajustée EIV de Shanken sont appliqué pour réaliser les régressions.

Résultats et conclusions

Tout d'abord, nous trouvons qu'il existe un effet de taille fort, mais aucun effet de valeur. L'effet de taille et le manque d'effet de valeur sont robustes lorsqu'ils sont contrôlés par le risque de détresse ainsi que sur l'ensemble de l'échantillon du marché boursier chinois. Et les effets sont également solides pour les proxys différentes du risque de détresse.

À partir des régressions chronologique, nous trouvons qu'il existe un effet de risque de détresse significatif, les portefeuilles qui ont le risque de détresse plus haut portent meilleure rentabilités sur le marché boursier chinois A-share, le pouvoir explicatif de DRF existe dans le top extrême (plus haut DR) et le bas (plus bas DR) groupes de portefeuille. Le pouvoir explicatif des trois facteurs de FF n'a pas de changement significatif avec ou sans DRF est présenté dans le modèle, nous pouvons donc conclure que les facteurs FF ne peuvent pas représenter DRF, le DRF explique plutôt les rentabilités chronologiques moyennes en combinaison avec des facteurs FF sur le marché boursier chinois A-share. Toutefois, le pouvoir explicatif supplémentaire de DRF est limité.

Par ailleurs, en comparant les résultats de régression selon en utilisant O-score et DLI comme les proxys du risque de détresse, la performance du facteur de risque de détresse basé sur le DLI semble légèrement meilleure que celui basé sur le O-score.

Nous fournissons des preuves à partir des régressions transversales que les coefficients sur DRF ne sont jamais un déterminant important des rentabilités moyennes, peu importe le DRF est régressé avec le marché bêta ou des trois facteurs de FF. D'autre part, peu importe le DRF est construit en utilisant O-score ou DLI comme le proxy, il existe une prime de taille robuste (prime de marché robuste lorsque DR est estimé en utilisant O-score). Ni le facteur de valeur HML ni le facteur de risque de détresse DRF est capable de capturer les variations transversale sur les rentabilités moyennes des actions.

Les études empiriques montrent que les facteurs FF ne perdent pas leur pouvoir explicatif en présence de DRF. Nous pourrions conclure que, bien que DRF est un facteur évalué pour déterminer les rentabilités chronologiques moyennes, il n'est pas le cas pour déterminer les rentabilités transversales moyennes. Les facteurs FF ne peuvent pas représenter DRF dans la section transversale du marché boursier chinois A-share.

Conclusions générales

L'objectif principal de cette thèse est d'explorer les facteurs de risque et les modèles des facteurs sur le marché boursier chinois A-share sur le contexte du modèle facteur de Fama-French.

Les résultats principaux de cette thèse sont présentés comme suit:

Tout d'abord, l'applicabilité du Modèle FF3F est ré-examiné pendant la période de juillet 2004 à mai 2015, en tenant compte de plusieurs caractéristiques spécials du marché boursier chinois. Les résultats empiriques montrent que le Modèle FF3F peut expliquer la majorité des variations de séries chronologiques des rentabilités des actions chinoises A-share, en utilisant la valeur marchande négociable pour pondérer les portefeuilles et la capitalisation boursière totale pour décider le point de rupture de taille, et le ratio B/P au lieu du ratio de B/M. Les résultats des régressions transversales sont conformes aux la plupart des études antérieures sur le marché boursier chinois, le marché bêta et le SMB sont des déterminants importants pour expliquer la variation transversale des rentabilités moyennes des actions. Au cours de la période d'échantillonnage, il existe une prime de marché négative et une prime de taille positive sur le marché boursier chinois A-share, mais aucune prime de valeur est trouvé. Ces résultats sont robustes avec l'ajustement EIV, et indépendants de l'intervalle de recherche.

L'applicabilité du dernier Modèle FF5F sur le marché boursier chinois A-part est aussi étudié au cours de la période de juillet 2010 à mai 2015. Afin de réaliser cette étude, trois séries de portefeuilles, six portefeuilles Taille-B/P pondérés en valeur, six portefeuilles Taille-OP pondérés en valeur et six portefeuilles Taille-Inv pondérés en valeur, sont construisons. Pour tous les trois séries de portefeuilles, les trois facteurs originaux – le facteur de marché, le facteur de taille et le facteur de valeur – possèdent toujours un pouvoir explicatif des séries chronologiques pour les rentabilités excédentaires attendus, en présence de facteurs de rentabilité et d'investissement. Il existe toujours un effet de taille dans tous les trois séries des portefeuilles et les rentabilités excédentaires sont négativement liés à la taille de l'entreprise; il existe l’effet de valeur dans les portefeuilles Taille-B/P, l'effet de rentabilité dans les portefeuilles Taille-OP et l'effet d'investissement dans les portefeuilles Taille-Inv. Le pouvoir explicatif du facteur RMW n'existe que dans les six portefeuilles Taille-OP. Le facteur CMA n’explique les rentabilités moyennes des portefeuilles que dans les groupes OP ou Inv extrêmes, par exemple le groupe OP faible, le groupe OP robuste, les groupes Inv conservatifs et agressifs. Tandis que les coefficients significatives sur CMA pour les portefeuilles Taille-B/P sont relativement dispersives.

D'après la comparaison des performances des modèles FF3F et FF5F en présence de facteurs de rentabilité et d'investissement, le Modèle FF5F ne peut pas capturer plus de variations des rentabilités des actions attendus que le Modèle FF3F, à l'exception des six portefeuilles pondérées en valeurs qui formés à partir de la taille et de la rentabilité opérationnelle (même si l'amélioration est limitée).

Dans le chapitre 2, nous examinons si les facteurs FF SMB et HML, sont les proxys d'innovations de variables d'état sélectionnées (rendement de dividende agrégée, taux de T-bonds en un mois, l'écart de terme et l'écart de défaut) qui décrivent, pendant la période recherche, les opportunités futures d'investissement sur le marché boursier chinois A-share. Les régressions chronologiques et les régressions transversales sont réalisées sur cinq modèles comparatifs. Les résultats empiriques indiquent que les facteurs FF ne perdent pas leur pouvoir explicatif, avec ou sans la présence des innovations des quatre variables d'état sélectionnés, à la fois dans les examens de séries chronologiques et les examens transversaux. Les résultats des régressions transversales révèlent également qu'il existe les primes significatives de risque de marché et de taille.. Ils montrent que l'information contenue dans l'innovation du rendements en dividende (IDIV) est totalement capturée par la combinaison du marché bêta et du facteur de taille Les facteurs FF ont pu jouer un rôle limité dans la captation d'opportunités d'investissement alternatives représentées par les innovations des quatre variables d'état sélectionnées.

Basé sur les découvertes, dans le chapitre 3, nous étudions si les facteurs FF sont des proxys de facteurs de risque de détresse et si différentes méthodes de construction des facteurs entraînent des résultats différents. Les résultats empiriques suggèrent qu'il n'y a pas de preuve significative que les facteurs FF représentent un risque de détresse sur le marché boursier chinois. La présence de DRF a peu d'effet sur le pouvoir explicatif de la série chronologique des trois facteurs FF, alors que le DRF, combiné avec les trois facteurs FF, peut partiellement expliquer de la rentabilité excédentaires moyenne des séries chronologiques. En comparant les résultats des régressions des séries chronologiques à partir de deux méthodes différentes, la performance du facteur de risque de détresse basé sur le DLI semble légèrement meilleure que celui basé sur le O-score. Cependant, le facteur de risque de détresse n'est pas un déterminant important des rentabilités transversales moyennes, et les facteurs FF ne peuvent pas représenter le facteur de risque de détresse dans la section transversale du marché boursier chinois A-share.

De plus, les études sur les facteurs de risque en Chine présentés dans cette thèse ont également fourni de nouvelles implications en pratique sur le marché boursier chinois:

Tout d'abord, en tenant compte de plusieurs caractéristiques spécials du marché boursier chinois, les résultats indiquent que le facteur de marché et le facteur de taille SMB sont des déterminants importants des rentabilités transversale des actions. Et l'existence de prime de taille et le manque de de prime de valeur sur le marché boursier chinois A-share sont indépendantes de la période de recherche. Basé sur les résultats du Modèle FF3F sur le marché boursier chinois, tels que les gestionnaires d'actifs, ils peuvent créer des portefeuilles qui inclinent vers le facteur de taille SMB plutôt que le facteur de valeur HML afin de gagner la taille de prime. De plus, les gestionnaires d'actifs ou les investisseurs individuels sont capable d'évaluer la performance potentielle d'un portefeuille par rapport au Modèle FF3F comme l’indice de référence.

Ensuite, selon les résultats de l'examen du Modèle FF5F sur le marché boursier chinois A-share, nous concluons que les facteurs de rentabilité et d'investissement ont un pouvoir explicatif supplémentaire limité et en comparaison avec le modèle original à trois facteurs, le Modèle FF5F n'a pas d'amélioration significative à expliquer la rentabilité excédentaire moyenne. Nos résultats est incompatible avec ceux sur le marché boursier américain. Similairement, si les investisseurs veulent investir sur le marché boursier chinois, il est préférable de sélectionner les portefeuilles construits en fonction de Modèle FF3F au lieu du Modèle FF5F. Cependant, si les investisseurs investissent sur le marché boursier américain, il est judicieux de choisir les portefeuilles construits selon le Modèle FF5F, puisque le Modèle FF5F est meilleur que le Modèle FF3F sur le marché boursier américain.

En plus, pendant l’étude d’explication économique des facteurs FF sur le marché boursier chinois, nous trouvons que les facteurs FF ne perdent pas le pouvoir explicatif en présence des innovations de variables d'état sélectionnées dans les régressions chronologiques et les régressions transversales sur le marché boursier chinois A-share. Comparer avec le modèle original FF3F, la présence d'innovations des variables d'état ne capture pas plus de variation de rentabilité moyenne. Les résultats indiquent que sur le marché boursier chinois, la construction de portefeuilles incline vers les innovations des quatre variables économiques ne peut pas générer une prime de risque supplémentaire. Le Modèle FF3F semble être le meilleur choix en pratique à ce jour sur le marché boursier chinois.

Enfin, dans chapitre 3, il est démontré que les facteurs FF ne sont pas les proxys du facteur du risque de détresse sur le marché boursier chinois, le facteur de risque de détresse, combiné avec les trois facteurs FF, explique plutôt la rentabilité moyenne excédentaire des séries chronologiques. Le modèle augmenté à quatre facteurs explique la variation chronologique des rentabilités moyennes des action meilleur que celui du Modèle FF3F. Dans ce cas, par exemple, si les portefeuilles sont construisent, en plus des facteurs FF, incline vers le facteur de risque de détresse imitant, on peut s'attendre à plus de rentabilité moyennes que les portefeuilles qui sont construisent uniquement basé sur des facteurs FF initiaux. Cependant, le bénéfice supplémentaire provient du facteur de risque de détresse est limité. Par ailleurs, les résultats peuvent également être réalisés par les entreprises pour estimer le coût de l'équité; par les investisseurs pour évaluer la valeur inhérente des actions et pour prendre leurs décisions.

Dans l'ensemble, afin de suivre le rythme des réformes de la Chine et de la mondialisation de son économie, le marché boursier chinois a connu un développement rapide et des réformes institutionnelles globales. Compte tenu des caractéristiques spécials, les rentabilités des actifs et ses déterminants pourraient être différents entre le marché boursier chinois et ceux des marchés boursiers développés (tels que le marché américain et le marché européen). Nos recherches actuelles ne peut pas de trouver l'explication économique du succès des facteurs FF sur le marché boursier chinois A-share, nous proposons donc d'examiner les facteurs de risque qui présentent les caractéristiques particulières du marché boursier chinois ou d'autres variables économiques relatif aux rentabilités des actions dans les recherches futures.

Introduction

Background

The factor models have been the dominant models in the asset pricing field for decades since the come up of Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Black (1972), a model which was aimed to estimate required return on assets under the main assumptions of Markowitz's portfolio theory. Even before the introduction of the popular CAPM, Markowitz (1959) proposed the use of a single-factor model to explain security returns. Sometimes referred to as index models, factor models often rely on the use of factor analysis to identify factors that influence asset returns.

The original CAPM can be regarded as the single-index factor model and has advantages of being easy to implement and interpret; however, it is criticized by many analysts for its assumptions and lack of explanatory power of stock market anomalies. Countless researchers have devoted themselves to develop a model that overcome the defects of CAPM, and the opponents of CAPM who see its lack of explanatory power, claim that there must be other factor(s) apart from excess market returns that derive the asset return. The asset pricing models that have more than one factor are called multifactor models.

Multifactor models can be divided into three types - fundamental, macroeconomic and statistical factor models. Connor (1995) gives a comprehensive overview of these three types of factor models: Fundamental factor models use the returns to portfolios associated with observed security attributes such as dividend yield, the book-to-market ratio, and industry identifiers; macroeconomic factor models use observable economic time series, such as inflation and interest rates, as measures of the pervasive shocks to security returns; statistical factor models derive their pervasive factors from factor analysis of the panel data set of security returns. The fundamental and macroeconomic factor models are models with known factors, while the statistical factor cannot directly observable or easily interpreted in contrast to known factors, they are also called latent factors. Latent factors are estimated by applying a statistical methodology known as factor analysis and the model generated is referred to as a factor model by statisticians, which is beyond the scope of this study.

The known factors normally used are observable economic, company and industry attributes and market data as “descriptors” (e.g. GDP growth, interest rate, price/earnings ratios, book-to-price ratios, estimated earnings growth, trading activity, and the business cycle). However, the descriptors are not factors, instead, they are the candidates for risk factors and are selected in terms of their ability to explain historical stock returns. The descriptors selected are then used to construct risk factors (economic or political factors or industry factors or country factors) and referred to as risk indices. The most popular factors today- Value, Growth, Size, Momentum- have been studied for decades as part of the academic asset pricing literature and the practitioner risk factor modeling research.

The underlying premise of these multifactor models is that certain common factors may be identified which capture the types of risk that are rewarded over investment horizons. Factor models are widely used by investors to link the risk exposures of the assets to a set of factors. In most of these models, the market index developed in the context of the CAPM is one of the factors, representing "market risk."

One of the fundamental multifactor models is the Arbitrage Pricing Theory (APT) introduced by Ross (1976). In this theory, most of the assumptions underlying the CAPM are relaxed. APT assumes that there are n factors that cause asset returns to systematically deviate from their expected values, however, the theory does not specify how large the number n is, nor does it identify what the factors are.

Another epoch-making paper was published by Fama and French (FF) in 1993, they deduce a three-factor model which includes a factor related to firm size (SMB) and a factor related to firm's book-to-market equity ratio (HML) in addition to market beta of CAPM, that is the well-known Fama-French Three-Factor Model (FF3F Model)[1]. They provide strong empirical evidence that the three-factor model captures most variation of cross-sectional excess stock returns in U.S. stock market. And the new factors have been demonstrated to add significantly to the prior understanding of returns based on the standard CAPM. Furthermore, the open source on the website of Kenneth R. French also facilitates following researchers. It is also worth noting that the FF model is one of the key reasons for Professor Fama being awarded the 2013 Nobel Prize in Economics. Since the came up of FF3F Model, an enormous amount of work has been implemented based on FF3F Model, such as focusing on finding new factors or examining how FF3F Model is doing on different stock markets all around the world. Nowadays, more researchers turn to seeking the economic underpinning behind the factors or the applications in practice.

Why the heat of factor models continues for decades and no any trace of decrease until now? There is a reason, the factor models, especially CAPM and FF3F Model, do not only occupy a pivotal place in the development of the asset pricing theory, but also make great

[1] Other multifactor models such as Burmeister-Ibbotson-Roll-Ross macroeconomic factor model developed by Burmeister et al. (1994), MSCI Barra fundamental factor model, Barclay Group Inc. bond factor model. In addition, the factor models developed by Haugen and Baker (1996a), and Chen and Zhang (2010) are also proven improvements on the CAPM-inspired single-index market model in explaining the cross-section of expected stock returns.

contributes to market practice and investment analysis. The factor models are implemented such as to select securities, construct a portfolio and control risk, quantify the risk exposure of a portfolio relative to a benchmark index, measure performance, and in portfolio manager evaluation.

Motivation

The factor models, are mentioned in a host of academic papers, and are widely used by portfolio managers, institutional investors, financial managers, and individual investors to predict asset returns; especially the original CAPM and FF3F Model which have each been recognized by the Nobel Committee, are among the most implemented factor models in the practice. For instance, a portfolio manager evaluates the impact of a series of broad factors on the performances of various securities; in this sense, a reliable factor model provides a valuable tool to assist portfolio managers with the identification of pervasive factors that affect large members of securities. Researchers use multifactor models to back-test and fine-tune strategies, and traders use these models to control investment risk over short horizons, etc.

The use of the factor models as a basis for research has become standard in the finance literature. Evidence of the fact that the FF factors are widely used can be found in the leading journals in the field, The Journal of Finance and Journal of Financial Economics. Both of these leading journals are ranked as A-star journals (the highest possible rating). They are commonly ranked as being in the top two or three finance journals worldwide. Most recently, Fama and French (2015a) propose a five-factor model aims at capturing the size, value, profitability, and investment patterns in average excess stock returns on U.S. stock market in the Journal of Financial Economics; and provide the international test of the five-factor model Fama and French (2017).

Furthermore, more empirical or practical evidence that factor models are widely used can be found in The Journal of Portfolio Management (JPM), which is one of the journals that offers cutting-edge research on asset allocation, performance measurement, market trends, risk management, portfolio optimization, and so on. Articles issued by JPM are not only from most renowned researchers but also from the renowned practitioners. Particularly, JPM issued a special issue of 2017 to celebrate its 40 years, which contains the most recent researches related to risk factors or factor models. Three articles (Bass et al. (2017), Cocoma et al. (2017), and Bender and Samanta (2017)) take the subject of factor-based portfolio allocation; four articles are on the basis of factor-based investing. Another two articles tend to the methodologies in studies of construction factor portfolios: Amenc et al.

(2017) provide two methods of building multifactor portfolios, while Liu (2017) proposes a pure quintile portfolio with new factor construction framework.

We list below several applications of factor models in practice:

- *Portfolio management*

The power of a multifactor model is that given the risk factors and the risk factor sensitivities, a portfolio's risk exposure profile can be quantified and controlled. A portfolio manager can also analyze their current risk and understand the size and location of their bets. On the other hand, factor models can be used to decompose portfolio risk according to common factor exposure and to evaluate how much of a portfolio's return was attributable to each common factor exposure. Consider a portfolio with more than 100 assets, instead of estimating the variance-covariance matrix of its assets, it only necessary to estimate the portfolio's factor exposures and the variance-covariance matrix of the factors, a computationally much easier task. Using a multifactor risk model and an optimization model, a portfolio that has the minimum active risk relative to its benchmark for a given number of assets held can be constructed. Similarly, a portfolio manager can construct a portfolio that tilts towards a specified factor, and has no material active exposure to any other factor. Furthermore, multifactor risk models allow a manager and a client to assess the potential performance of a portfolio or trading strategy relative to a benchmark. In sum, multifactor models can be used to analyze portfolio risk, construct portfolios that optimally trade off risk with expected returns, and analyze skill and value added associated with past returns. Consequently, the factor models offer a useful extension of the CAPM and the APT because they advance our understanding of how key factors influence portfolio risk and return.

- *Required return estimation and equity valuation*

The factor models are used largely to estimate the required return on equity, given the relevant risk. That is, the model has the purpose of estimating normal risk-adjusted returns. Estimating normal risk-adjusted returns are also required for a number of purposes including setting regulated returns and for the purposes of determining whether a portfolio or trading strategy shows out-performance on a risk-adjusted basis. The use of the factor models, especially FF3F Model, as a basis for estimating required returns has become standard in the finance literature. For example, the issues of February 2014 and December 2013 of the Journal of Finance feature five articles that use the FF factors for the purposes of estimating required returns. The volume (2014) of the Journal of Financial Economics features four articles that use the FF factors for the purposes of estimating required returns. Indeed, the use of the Fama-French factors, for the purpose of estimating the required return on equity, is so widespread in the academic literature, its use as a measure of normal returns has become a matter of course.

If investors expect a return of a particular stock higher than required return, then the stock is undervalued; in contrast, if expected return is less than required rate of return, then the stock is overvalued. The required rate of return is a component in many of the metrics and calculations used in corporate finance and equity valuation.

The main goal of equity valuation is to estimate its inherent value. For investors, they are concerned with the value of their investment, they all want to make sure that the product they buy or sell is worth the value (price) they pay or receive. Inherent value is the "true" or "real" value of an asset that is obtained and supported by rational, hypothetical, unbiased mathematical models that consider all relevant factors that drive the value of an asset. However, the inherent value is unobservable, so the best we can do is to estimate it using asset pricing models. Such, the factor models are one category of the models that are supposed to estimate the inherent value of common equities[2]. Inherent value can differ from market value, in which case stock becomes overvalued or undervalued depending on whether the inherent value is lower or higher than market value.

Equity valuation is a central part in many activities such as stock selection, stock analysis, inferring market expectations, evaluation of corporate events (mergers and acquisitions, divestitures, spin-offs), and private business valuation. Equity portfolio managers do equity valuation of companies they consider including in a portfolio. Active managers, in particular, do valuation because their primary goal is to identify mispriced (undervalued or overvalued) securities. Investment banks who play an intermediary role in corporate events, for example in mergers and acquisitions, also carry out the valuation of the target company. A stock analyst evaluates the stocks she follows to give recommendations (buy, hold, sell). Analysts or researchers also frequently use valuation models to extract (infer) market expectations. For example, an analyst may input the current market prices and interest rates, dividends, and other factors, into an equity valuation model in order to find what growth rate the market implies.

- *Corporate finance practice and the cost of equity estimation*

The cost of capital is the required return necessary to make a capital budgeting project and includes the cost of debt and the cost of equity. The factor models are generally used to measure the cost of equity (COE). COE is the return that stockholders require for their investment in a company. A firm's COE represents the compensation that the market

[2] The dividend discount model and the free cash flow to equity model are also two well-known models that are supposed to estimate inherent value of common equities.

demands in exchange for owning the asset and bearing the risk of ownership. Common shareholders expect to obtain a certain return on their equity investment in a company, the equity holders' required rate of return is a cost from the company's perspective. The cost of equity is basically what it costs the company to maintain a share price that is theoretically satisfactory to investors. On this basis, the most commonly accepted method for calculating the cost of equity comes from CAPM and FF3F Model.

If you ask participants involved in capital allocation decisions at large corporations "What model do you use to estimate the cost of equity capital?" the most common answer is the CAPM. However, when you evaluate the responses in detail you observe a large proportion of respondents make adjustments to the CAPM estimate of the cost of equity capital to account for other risk factors. What is proposed in the use of the FF model is an objective measurement of risk that is consistent with the empirical evidence on stock returns.[3]

In 1999, a survey was conducted amongst 392 representatives of large corporations in the U.S. (Graham and Harvey, 2001). In 2002, the same set of questions was posed to 313 representatives of large corporations in the U.K., the Netherlands, Germany, and France (Brounen et al., 2004). In response to the question, "How do you determine your firm's cost of equity capital?" the percentage of respondents who said they always or almost always used the CAPM ranged from 34% to 73% across the five countries. However, this is not the only evaluation technique used in estimating the cost of equity. Another alternative answer was "using the CAPM but including some extra risk factors." The proportion of respondents who stated that they always or almost always incorporated extra risk factors into the CAPM ranged from 15% to 34%, with an aggregate percentage of 28%. As SFG report states that if corporate finance practice is used to determine how regulation should evolve, the benchmark would be to use the factor models (the CAPM with additional risk factors).

- *Factor-based investment*

Factor investing has become a widely discussed part of today's investment canon. Investment researchers use multifactor risk models to run controlled back tests of future investment strategies. For this, their needs are similar to those of portfolio managers. They need to implement strategies optimally on historical data and understand the subsequent performance of those strategies. Researchers can use back tests to enhance their strategies. They can also use performance analysis and portfolio risk characterization to improve their understanding of the bets they are testing. The evidence that factor-based investment is in vogue nowadays can also be found in the latest special issue (2017) of Journal of Portfolio Management, two articles (Dimson et al. (2017) and Kim et al. (2017)) focus on factor-

[3] SFG Consulting report of the Fama-French model.

based investing and two articles (Podkaminer (2017), Alford and Rakhlin (2017)) about smart beta which is a currently popular factor-based investment strategy. For example, MSCI has created a family of factor indexes (smart beta indexes) that provide access to six solidly grounded factors—value, low size, low volatility, high yield, quality, and momentum.

Of course, those mentioned above are not all the applications of factor models in practice. Other examples like pension plan sponsors can use multifactor risk models to coordinate their multiple managers. Portfolio risk characterization allows them to understand any gaps or overlaps among their managers or in their asset allocation mixes. Plan sponsors also use performance analysis to assess their managers' value added and to check on their managers' styles.

The extensive research and widely practical use of factor models are two of the motivations for this dissertation, another one is the Chinese stock market. Significant economic growth in China over the past few decades has been universally acknowledged, China now has the second-largest economy in the world, and is the biggest developing country. The Chinese stock market, established in 1990, is one representative of the emerging markets with relative short history. Its development along with its immaturity has attracted considerable attention from researchers, and also has brought into question of whether the asset pricing models such as FF model are also applicable to its domestic markets.

Therefore, both the popular of factor models and the attractive emerging stock market prompt the original intention in the study of factor models (risk factors) on Chinese stock market. One may say that this again another study of factor models on the basis of FF3F Model, but what we want to emphasize is that FF3F Model has become the cornerstone of factor studies, the research on factor models have been a hot research topic for decades, and it will continue to be a key topic of asset pricing field in the future.

Objective and Structure of Dissertation

The work presented in this dissertation contains three chapters, mainly explore the risk factors on Chinese stock market on the basis of FF3F Model, and the studies of each chapter are closely linked while relatively independent as well. The success of FF3F Model on U.S. stock market impels the studies of the applicability in other developed or emerging markets all around the world. China has attracted more and more researchers’ attention, the applicability of FF3F Model on Chinese stock market has also been a hot topic for years. This dissertation begins with re-testing the FF3F Model using data of Chinese A-share

(CNAS) stock market in order to answer the question that whether FF3F Model is applicable on CNAS stock market, and the following work is then unfolded on the basis of FF3F Model.

Chapter 1 re-investigates the FF3F Model and explore the latest FF5F Model on CNAS stock market, aims to examine the applicability of both models in China. Furthermore, we compare the regression results of both models to test whether FF5F performs better than FF3F Model in capturing the variation of average stock returns as they are proved so in U.S. market. It is worth noting that we take into account several special features of Chinese stock market that are non-negligible in order to benefit a more reliable research results.

To implement the investigation, we construct all five factors – excess market return, size factor SMB, value factor HML, profitability factor RMW and investment factor CMA using data of CNAS stock market, Fama-MacBeth (1973) two-stage approach is applied for the time-series regression (TSR) and cross-sectional regression (CSR). Since the Fama-MacBeth (FM hereafter) two-stage approach caused the classical errors-in-variables problem, the correction procedure proposed by Shanken (1992) is applied.

Though the great achievement of FF factor models, it is also one of the most controversial asset pricing model, mainly for its purely empirical-based considerations and lack of theoretical underpinnings. The success of FF3F Model on CNAS stock market stimulates the chasing down for economic foundation of FF factors, especially the SMB factor. In chapter 2, we proceed with the research in line with one of the dominant explanations, which is based on time-varying investment opportunities in the context of ICAPM. We examine whether FF factors proxy for the innovations of selected state variables that describe the future investment opportunities on CNAS stock market, and we choose four economic variables in accordance with Petkova (2006): aggregate dividend yield, one-month T-bill rate, term spread and default spread, which in order to model two aspects of investment opportunity set – the yield curve and the conditional distribution of asset returns.

To extract the innovation terms, the vector auto-regression (VAR) process has been utilized; and as Campbell (1996) emphasizes that "it is hard to interpret estimation results for a VAR factor model unless the factors are orthogonalized and scaled in some way", we orthogonalize innovations of state variables to the excess market return, which is the first element of the vector in VAR process. The Fama-MacBeth (1973) two-stage approach is then implemented for both TSR and CSR for the research.

In chapter 3, we choose distress risk factor as the augmented factor of the original FF3F Model among plenty risk factors that have been discovered. Since firm's distress risk is an important indicator of a firm's performance and is also one of the most concerned characteristics by investors and firms. What's more, the financial distress risk has been proved closely related to stock returns and the viewpoint of value effect is regarded as the distress risk effect are proposed by time-series literature.

The main objective is to test whether distress risk factor FF factors are proxies for distress risk on CNAS stock market during the period July 2005 to May 2015, if not, whether augmented four-factor model better explains expected average stock returns than FF3F Model. Especially, we apply both accounting-based (Ohlson's O-score) and market-based (Vassalou and Xing's DLI) models to measure the financial distress in order to identify whether different methods of predicting distress risk matter to the empirical results. In addition, the relationship between stock returns and distress risk, and whether the size and value effects are related to distress risk have also been examined on CNAS stock market.

Contributions and Discussion

Though it seems that we are one of the countless studies of testing FF3F Model on Chinese stock market initially in Chapter 1, actually we consider several special features of Chinese stock market and examine not only the time-series but also cross-section validation of FF3F Model. Furthermore, we examine the performance of the latest FF5F Model using data of CNAS stock market, while the comparisons between the performance of both models on CNAS stock market, and the performance of same models between Chinese and U.S. stock market are also implemented.

Despite the extensive evidence that confirm the capability of FF factors in capturing variations of expected average stock returns on Chinese stock market, however, to the best of our knowledge, few studies have authentically focused on the economic underpinning behind FF factors in China. We are the advance ones who explore one of the most popular explanations which is based on time-varying investment opportunities in the context of ICAPM, examine whether FF factors proxy for innovations of selected economic variables on Chinese stock market.

Moreover, developing an early warning system for prediction of firms' financial distress has been a hot topic over the years in China; the research on Chinese market are mainly focused on testing the predictive accuracy of commonly used models in estimating distress risk and measuring default risk of Chinese companies without studying the relationship between default risk and stock returns. We are also the rare ones who propose a mimicking distress factor and investigate the distress risk factor in the frame of FF3F Model.

Overall, our research has new implications in practice (such as for the factor-based investment and assessing the performance of portfolios) on Chinese stock market. The

Chinese stock market developed along with extraordinary economic growth and overall institutional reforms so that it might be much different from the mature stock markets such as U.S. stock market. Therefore, for further research, it might be more appropriate to construct risk factors that feature Chinese own characteristics and introduce which to the factor model, thus help researchers to understand the real economic meaning of FF factors on Chinese stock market.

1 Fama-French Five-Factor Model vs. Fama-French Three-Factor Model in China

1.1 Reviews of the main asset pricing theories and models 12

1.2 Retrospective of empirical work of Fama-French factor models 16

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This chapter re-examines the applicability of Fama-French Three-Factor Model by constructing Fama-French factors on Chinese A-share stock market, considering several special features of Chinese stock market. In addition, this chapter also investigates the latest FF5F Model using data of Chinese stock market by apply Fama-MacBeth two-stage approach. Empirical results answer the questions of whether Fama-French Three-Factor Model explain time-series and cross-sectional variation of average excess stock returns over the sample period; whether the profitability and investment factors have extra explanatory power and whether Fama-French Five-Factor Model performs better than Fama-French Three-Factor Model on Chinese A-share stock market. Furthermore, the comparisons of the empirical results between Chinese stock market and U.S stock market are conducted as well.

1.1 Reviews of the main asset pricing theories and models

1.1.1 The evolution of the asset pricing models

The history of the theory of the financial asset pricing can be traced back to Bernoulli's famous St Petersburg paper of 1738, since then, researchers have been focusing on this subject for centuries. In the early life of financial fields, describing the market environment and valuing individual securities are the emphasis, which are transformed with the appearance of Markowitz (1952) paper on portfolio selection. After the birth of Portfolio Selection theory, the discussions of pricing on the financial asset can also be divided into two different periods. Before the 1980s, researchers mainly focus on pure theory, applying Markowitz's optimal selection theory into their research. But after the 80s, as Sharpe (1964), Lintner (1965) and Black (1972)'s CAPM becoming a research paradigm, the focal point has transferred to two directions: extending the original CAPM and the empirical research of the model.

The initial extension involved extending the single-period model into a multi-period framework, which turns out to be one of the major developments of modern finance. Merton (1973a) proposes an Intertemporal CAPM (ICAPM) and shows that the classical CAPM would not in general hold in continuous time periods. Breeden (1979)'s Consumption CAPM (CCAPM) links the consumption and stock returns and the model relies on the aggregate consumption in order to understand and predict future asset prices instead of the market portfolio's return in the traditional CAPM.

Meanwhile, Jensen et al. (1972) performed the first strict tests of the original CAPM by constructing ''two-pass'' methodology. While the researchers were trying by all means to test the CAPM, Roll (1977) shows that the CAPM never could be tested unless the market portfolio were known with certainty. Even many researchers have tried to tackle the Roll's critique, unfortunately, it turns out that CAPM seems not to hold and there are amounts of evidence that other risk factors also affect the stock returns. The factors will be listed in section 1.2 below.

Around the same time Ross (1976) develops the Arbitrage Pricing Theory (APT) as an alternative model that could potentially cover the CAPM's short falls, while still retaining the underlying message of the latter. The APT starts by assuming that there are n factors that cause asset returns to systematically deviate from their expected values, however, the theory does not specify how large the number n is, nor does it identify the factors. Empirically, the APT has been investigated by using either factor analytic methods (Roll and Ross, 1980), to estimate multiple measures of systematic risk, or pre-specified macroeconomic factory (Chen et al., 1986), in which the studies look at pricing relative to a set of observable macroeconomic variables, or factors, selected primarily based on economic intuition.

1.1.2 Reviews of Fama-French Three-Factor Model

The facts that there are other risk factors can also explain the variation of stock returns have been verified by a huge number of research. The factors which are already been verified include the earnings/price ratio (Basu, 1977), company size (Banz, 1981), book-to-market equity (Fama and French, 1992) and a variety of other systematic influences on asset price (Dimson and Mussavian, 1998). An asset pricing model who can better explain the risk and the stock returns is demanded in the financial market and many researchers are devoted to do this work. Among which, Fama and French (1993) [hereafter FF] deduce a three-factor model as an alternative way to predict the stock returns or an extension of the original CAPM, and their model not only reveals the primary factors that drive stock return but also provides a strategy for using those factors in the portfolio for a potentially higher expected long-term return, which makes it an extraordinary model and also represent another important progress in the history of asset pricing development.

In fact, Fama and French (1992) studied the joint roles of market beta, size, leverage, Earnings/Price (E/P) ratio and book-to-market equity (B/M) ratio in the cross-section of average stock returns for NYSE, Amex and NASDAQ stocks over the period 1963-1990. In that study, the authors find that beta has almost no explanatory power. On the other hand, when used alone, size, E/P, leverage and B/M ratio have significant explanatory power in explaining the cross-section of average returns. When used jointly, however, size and B/M equity ratio are significant and they seem to absorb the effects of leverage and E/P in explaining the cross-section average stock returns. Fama and French (1992) therefore argued that if stocks are priced rationally, risks must be multidimensional.

Fama and French (1993)'s analysis was extended to both stocks and bonds. Monthly returns on stocks and bonds were regressed on five factors: returns on a market portfolio, a portfolio for size and a portfolio for the book-to-market equity effect, a term premium and a default premium. For stocks, the first three factors were found to be significant and for bonds, the last two factors. As a result, Fama and French (1993) construct a three-factor asset pricing model for stocks that includes the conventional market beta and two additional risk factors related to size and book to market equity. They find that this expanded model captures much of the cross section of average returns amongst US stocks.

Compared to the original CAPM, FF3F Model shows that the expected return on a portfolio in excess of the risk-free rate is explained by the sensitivity of its return to three factors:

first, the excess return of the market portfolio; second, the difference between the returns of the small size portfolio and those of the big size portfolio (SMB) and third, the difference between the returns of the high book-to-market portfolio and those of the low book-to-market portfolio (HML). The model is as followed:

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t} \tag{1.1}$$

Where:

$R_{i,t}$ is the value-weighted return on portfolio *i* in period *t*;

R_f is the risk-free rate;

$R_{M,t} - R_f$ is the difference between the return of market portfolio (market beta) and the return of risk-free rate; *SMB* is the size factor (small minus big) and *HML* is the value factor (high minus low);

b_i is the coefficient for the excess return of the market portfolio;

s_i is the coefficient for the excess return of portfolios with small equity class over portfolios of big equity class;

h_i is the coefficient loading for the excess average returns of portfolios with high book-to-market equity class over those with low book-to-market equity class;

$e_{i,t}$ is the error term for portfolio *i* at time *t*.

1.1.3 Reviews of Fama-French Five-Factor Model

Motivated by the valuation theory and recent empirical findings on the strong profitability and investment effects in asset returns[4]. Fama and French (2015a) propose a five-factor model contains the market factor and factors related to size, book-to-market equity ratio, profitability and investment, which performs better than the three-factor model of Fama and French (1993):

[4] Recently, Novy-Marx (2013) identifies a proxy today that predicts expected earnings tomorrow - the profitability factor, which is strongly related to average stock return, and the investment factor was documented by Aharoni et al. (2013), see also Titman et al. (2004), although it has a high correlation with the value and profitability factors, the investment effect is perhaps half as strong, but it is still reliable and significant.

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{i,t} \qquad (1.2)$$

From equation (1.2), it is obvious that the five-factor model has two more factors than the three-factor model, RMW and CMA. RMW is the factor related to firm's profitability which is the difference between the returns on portfolios of robust (high) profitability and weak (low) profitability firms. CMA is the one related to investment, which is the difference between the

returns of conservative (low) investment portfolios and aggressive (high) investment portfolios.

In this paper, Fama and French suggest that the theoretical starting point is the "Dividend Discount Model":

$$m_t = \sum_{\tau=1}^{\infty} E(d_{t+\tau}) / (1 + r)^{\tau} \qquad (1.3)$$

where m_t is the share price at time *t*, $E(d_{t+\tau})$ is the expected dividend per share for the period $t+\tau$, and r is (approximately) the long-term average expected stock return or, more precisely, the internal rate of return on expected dividends. This model states that the value of a stock today will be the sum of the discounted present value of all its future dividends.

With a little bit manipulation, the dividend per share $d_{t+\tau}$ is the difference between $Y_{t+\tau}$, the equity earnings for period $t+\tau$, and $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$, which is the change in book equity. Then the dividend discount model (equation (1.3)) becomes:

$$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) / (1 + r)^{\tau} \qquad (1.4)$$

Divided by book equity at time t gives,

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) / (1 + r)^{\tau}}{B_t} \qquad (1.5)$$

Equation (1.5) implies three statements about expected stock returns.

- Firstly, fix everything except the expected stock return *r* and the current value of the stock M_t, a lower market value M_t, or equivalent to a higher B/M ratio implies a higher expected stock return.

- Next, fix everything except the expected earnings $Y_{t+\tau}$ and expected stock returns r, more profitable companies which with higher expected earnings have higher expected returns.
- Finally, controlling for the expected growth $dB_{t+\tau}$ (investment) and expected stock returns while fixing other elements, firms with higher expected growth in book equity implies a lower expected return.

The dividend discount model and its transformation indicate the relationship between the variables and average asset returns. FF point out that the nature of equation (1.3) and equation (1.5) is the reason why they choose profitability and investment factors to augment the model.

The construction of profitability factor and investment factor and the portfolios are demonstrated in the following section.

1.2 Retrospective of empirical work of Fama-French factor models

1.2.1 Overviews of the data and methodologies of FF factor models

1.2.1.1 Construction of Fama-French three factors and portfolios

To do the regressions, Fama and French use stocks in the intersection of American stock markets (1963-1990), NYSE, AMEX, and NASD to construct the portfolios on size and B/M ratio, among which, financial firms and firms with negative B/M equities are eliminated from the sample. To obtain the size and value portfolios, they use a firm's market capitalization at June of year *t* to measure its size and at the end of December of year *t-1* to compute book-to-market equity ratio. So in June of each year t, the stocks are sorted into two size groups: small firms (S) and big firms (B), according to their market value. They also break stocks into three B/M equity groups at each December of year *t-1*: low B/M equity ratio (L), medium B/M equity ratio (M) and high B/M equity ratio (H) firms, according to the breakpoint 30% and 70% of values of B/M equity for all the stocks.

After these steps, they have two size groups and three B/M equity groups at each year *t*. The intersections of these groups are constructed into six portfolios: small low (SL), small medium (SM), small high (SH), big low (BL), big medium (BM), and big high (BH) portfolios. For instance, The SL portfolio contains stocks in the small size (S) group which meanwhile have low B/M equity ratio (L); the BH portfolio contains stocks in the big size (B) group that also in the high B/M equity group (H). The value-weighted monthly returns are calculated from July of year *t* to June of year *t+1*, during which the portfolios remain the same, and the portfolios are reconstructed in July of year *t+1* (B/M ratio should exist at December of year *t-1*).

Finally, the Fama-French three factors obtain as follows. The market factor is the excess market return which is computed as the difference between the value-weighted returns of all A-shares and the risk-free rate. The SMB factor is then the difference between the simple average of the monthly returns of the three small-size portfolios (SL, SM, and SH) and the simple average of monthly returns of the three big-size portfolios (BL, BM, and BH). Similarly, HML is equal to the simple average monthly return of the two portfolios with high book-to-market equity (SH and BH) minus which of the two portfolios with low book-to-market equity (SL and BL).

$$\begin{aligned} SMB = & \frac{1}{3}(\, Small\ Low + Small\ Medium + Small\ High) \\ & -\frac{1}{3}(\, Big\ Low + Big\ Medium + Big\ High\,) \end{aligned} \tag{1.6}$$

$$HML = \frac{1}{2}(\, Small\ High + Big\ High\,) - \frac{1}{2}(\, Small\ Low + Big\ Low\,) \tag{1.7}$$

1.2.1.2 Construction of profitability factor and investment factor

Similar to FF three factors that are constructed using the 6 value-weighted portfolios formed on size and book-to-market equity. The Fama-French 5 factors (2x3) are constructed using the 6 value-weight portfolios formed on size and book-to-market (Size-B/M portfolios), the 6 value-weight portfolios formed on size and operating profitability (Size-OP portfolios), and the 6 value-weight portfolios formed on size and investment (Size-Inv portfolios). The Size-OP portfolios and Size-Inv portfolios are formed in the same way as the Size-B/M portfolios, except the second sort variable is operating profitability or investment.

The operating profitability (OP) for June of year *t* is calculated as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in *t-1*. The Investment portfolios are formed on the change in total assets from the fiscal year ending in year *t-2* to the fiscal year ending in *t-1*, divided by *t-2* total assets at the end of each June using NYSE breakpoints. To be more clear:

$$OP = (\,Gross\ Profitability - Interest\ Expense - Selling,\ General\ and\ Administrative\ Expenses\,)\,/\,(\,Book\ Equity\,)_{t-1} \tag{1.8}$$

$$Inv = \left[(\,Total\ Asset\,)_{t-1} - (\,Total\ Asset\,)_{t-2}\right] / (\,Total\ Asset\,)_{t-1} \tag{1.9}$$

Where,
OP represents the operating profitability;
$Gross\ Profitability$ equals annual revenue minus the cost of goods sold;
$Book\ Equity$ is book value of equity;
Inv represents the investment opportunities;
$(\,Total\ Asset\,)_{t-1}$ is the total value of assets in year *t-1*;
$(\,Total\ Asset\,)_{t-2}$ is the total value of assets in year *t-2*.

The size breakpoint for year *t* is the median NYSE market equity at the end of June of year *t*. The construction of portfolios on OP and investment are similar with that of portfolios on book-to-market equity. At the end of each June, the firms are sorted into three OP portfolios based on the breakpoints of the 30th and 70th NYSE percentiles, and the three investment portfolios are formed in the same way using NYSE breakpoints-30th and 70th NYSE percentiles.

Then at the end of each June, the intersections of two portfolios formed on size - small (S) and big (B), and three portfolios formed on profitability – weak profitability (W), neutral profitability (N) and robust profitability (R) are constructed into six “Size-OP” portfolios: SW, SN, SR, BW, BN and BR[5]. Similarly, the “Size-Inv” portfolios, which are also constructed at the end of each June, are the intersections of two portfolios formed on size and three portfolios formed on investment- conservative investment (C), neutral investment (N) and aggressive investment (A). Thus, the six Size-Inv portfolios are constructed: SC, SN, SA, BC, BN, and BA[6].

In Fama-French five-factor (FF5F) Model, the market factor and value factor remain the same as in the three-factor model, while the size factor SMB need to be reconstructed with profitability and investment factors, which is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios. The two additional

[5] Portfolio SW contains firms with small size and weak profitability, SN contains firms with small size and neutral profitability, SR contains firms with small size and robust profitability, similarly to BW, BN and BR, which contains firms with big size and weak profitability, neutral profitability and robust profitability separately.
[6] Portfolio SC contain firms with small size and conservative investment, SN contains firms with small size and neutral investment, SA contains firms with small size and aggressive investment, similarly to BC, BN and BA portfolios.

factors are directed at capturing the profitability and investment patterns, which are indicated by RMW and CMA. As shown in equation (1.14) and equation (1.15), RMW is the difference between returns on portfolios with robust and weak profitability, and CMA is the difference between returns on portfolios of the stocks of low and high investment firms, which is called conservative and aggressive, separately. In detail:

$$\begin{aligned} SMB_{B/M} &= \frac{1}{3}(\,Small\ Low + Small\ Medium + Small\ High) \\ &\quad - \frac{1}{3}(\,Big\ Low + Big\ Medium + Big\ High\,) \end{aligned} \tag{1.10}$$

$$\begin{aligned} SMB_{OP} &= \frac{1}{3}(\,Small\ Robust + Small\ Neutral + Small\ Weak) \\ &\quad - \frac{1}{3}(\,Big\ Robust + Big\ Neutral + Big\ Weak\,) \end{aligned} \tag{1.11}$$

$$\begin{aligned} SMB_{Inv} &= \frac{1}{3}(\,Small\ Conservative + Small\ Neutral + Small\ Aggressive) \\ &\quad - \frac{1}{3}(\,Big\ Conservative + Big\ Neutral + Big\ Aggressive\,) \end{aligned} \tag{1.12}$$

$$SMB = \frac{1}{3}(\,SMB_{B/M} + SMB_{OP} + SMB_{Inv}\,) \tag{1.13}$$

$$RMW = \frac{1}{2}(\,Small\ Robust + Big\ Robust) - \frac{1}{2}(\,Small\ Weak + Big\ Weak\,) \tag{1.14}$$

$$\begin{aligned} CMA &= \frac{1}{2}(\,Small\ Conservative + Big\ Conservative) \\ &\quad - \frac{1}{2}(\,Small\ Aggressive + Big\ Aggressive\,) \end{aligned} \tag{1.15}$$

1.2.2 Reviews of the empirical tests for Fama-French Three-Factor Model

1.2.2.1 Empirical results of FF on some developed countries' stock markets

Fama and French (1992) show that two easily measured variables, size and book-to-market equity, seem to capture the cross-section of average stock returns. Then the article of FF (1993) extends the FF's (1992) study by using a time-series regression (TSR) approach, and the analysis was extended to both stocks and bonds markets. Monthly returns on stocks and bonds were regressed on five factors: returns on a market portfolio, a portfolio for size and a portfolio for the book-to-market equity effect, a term premium and a default premium. For stocks, the first three factors were found to be significant. As a result, FF (1993) construct a three-factor asset pricing model for stocks that composed by the conventional market beta and two additional risk factors related to size and book to market equity. They find that this model captures much of the cross section of average returns of U.S. stock markets.

In addition, they also find that the slopes on SMB for stocks are related to size, in every B/M ratio quintile of stocks, the slopes on SMB decrease significantly from smaller-size quintiles to bigger-size quintiles. Similarly, the slopes on HML are related to B/M ratio, in each size quintile, slopes of HML increase from the lower B/M quintile to the higher B/M quintile. Researchers have suggested the following possible explanations for the size effect. Small firms' stocks are more illiquid and trading in them attract greater transaction costs; there is also less information available about small firms and therefore the cost of monitoring a portfolio of small stocks will generally be greater than that of a portfolio of large firms, and also given that small shares trade less frequently, their beta estimates might be less reliable. However, all these remain hypothetical explanations for the size effect, as there is no rigorous theory explaining convincingly why the size effect should be present. The B/M ratio effect shows that average returns are greater the higher the book-to-market value ratio and vice versa. It is also referred to as the value premium. The high book value firms are underpriced by the market and are therefore good buy and hold targets, as their price will rise later. This anomaly undermines the semi-strong form efficiency of the market. These two variables explain average return differences across portfolios that cannot be accounted for by beta.

Fama and French (1995) analyze the characteristics of firms with high B/M ratio and those with low B/M ratio. They find that firms with high B/M ratio tend to be persistently distressed and those with low B/M ratio are associated with sustained profitability. They conclude that the returns to holders of high B/M ratio stocks are therefore a compensation for holding less profitable and riskier stocks. They show that book-to-market equity and slopes on HML in the three-factor model proxy for relative distress. Weak firms with persistently low earnings tend to have high B/M ratio and positive slopes on HML; strong firms with high earnings have low B/M ratio and negative slopes on HML.

Similarly, Chan and Chen (1991) posit that small and large firms have different risk and return characteristics. Small firms on the New York Stock Exchange are firms that have not been doing well, are less efficiently managed and are highly levered. As a result, small firms tend to be riskier than large firms and that risk is not captured by the market index. After introducing multiple risk exposures to the market index; a leverage index and a dividend-decrease index to mimic the marginal firms, the size effect loses its explanatory power. Risk exposures to these indices are as powerful as size in explaining average returns of size-ranked portfolios.

However, Kothari et al. (1995a) and MacKinlay (1995a) argue that a substantial part of the premium is due to survivor bias and data snooping. The data source for book equity contains a disproportionate number of high B/M firms that survive distress, so the average return for high B/M equity firms is overstated. The data snooping hypothesis posits that researcher's fixation to search for variables that are related to average return, will find variables, but only in the sample used to identify them. But a number of papers have weakened and even dismissed the survivorship-bias and the data snooping hypothesis. For instance, Lakonishok et al. (1994a) find a strong positive relation between average returns and B/M ratio for the largest 20 percent of NYSE-Amex stocks, where survivor bias is not an issue. Similarly, FF (1993) find that the relation between B/M ratio and the average return is strong for value-weight portfolios. As value-weight portfolios give most weight to larger stocks, any survivor bias in these portfolios is trivial. There are also are many studies using different sample periods on US data and samples in different countries confirming the existence of the size and book-to-market equity effects. FF (1998) provide additional valuable out-of-sample evidence. They tested the FF three-factor model in thirteen different markets over the period 1975 to 1995. They find that 12 of the 13 markets record a premium of at least 7.68 percent per annum to value stocks (high B/M ratio). Seven markets show statistically significant B/M betas.

Maroney and Protopapadakis (2002) test the FF three-factor model on seven stock markets of Australia, Canada, Germany, France, Japan, the UK and the US. The size effect and the value premium survive for all the countries examined. They conclude that the size and B/M effects are international in character. Using a Stochastic Discount Factor (SDF) model, and a variety of macroeconomic and financial variables, do not diminish the explanatory power of B/M ratio and market value. Their evidence suggests that the B/M and size effects are not artifacts of the inadequacies of the augmented CAPM as an asset-pricing model or of omitting macroeconomic and financial variables. The positive relation of returns with B/M and their negative relation with market value remain strong under a general SDF model.

Faff (2001) uses Australian data over the period 1991 to 1999 to examine the power of the FF3F Model. He finds strong support for the FF3F Model, but a significant negative rather than the expected positive, premium, to small size stocks. Faff (2001) concludes that his results appear to be consistent with other recent evidence of a reversal of the size effect. Gaunt (2004) studies the FF3F Modl in the Australian setting and provides further out of sample (non-US) tests of the model. The study covers the period 1991 to 2000 of firms listed on the Australian Stock Exchange. He finds that beta risk tends to be greater for smaller companies and those with lower BM ratios. Contrary to FF, the betas are on average significantly less than one. There is also evidence of the value effect increasing monotonically from the lowest to the highest book-to-market equity portfolios. There is a monotonic increase of loadings on the SMB factor as well when moving from the largest to the smallest portfolios. They find large and positive intercepts for the small portfolios. The explained variation as measured by the adjusted R^2 is also much higher compared to the CAPM. The author concludes that the three-factor model provides a better explanation of observed Australian stock returns than the CAPM.

Numerous studies examined various global markets following research of FF. Studies on the UK market by Chan and Chui (1996) fail to find a significant beta-return relationship. Subsequent studies by Hung et al. (2004) and Morelli (2007), again examining the UK market all provide further evidence against an unconditional relationship between beta and returns. Morelli (2007) find a significant relationship between beta and returns in the presence of size and book-to-market equity, but the author documents that size is not a significant risk variable, whereas B/M ratio is a significant determinant of security return on UK market. Studies of other European markets including, Lilti and Montagner (1998) in the French market, Isakov (1999) in the Swiss market, and Elsas et al. (2003) in the German market, all find beta to be a significant risk measurement

1.2.2.2 Summary of empirical results in emerging Asian markets

Most Asian stock markets are emerging market which draws researchers' attentions, and it's interesting and meaningful to study the FF3F Model which is well performed in U.S. on the emerging Asian markets. Researches are done which concerning Fama-French factors and stock market anomalies on the emerging stock market in Asia: such as India, Thailand, Indonesia, Malaysia, Singapore, Korea, Vietnam and Hong Kong.

Early in 1995, Claessens et al. (1995) study the cross-section of stock returns from twenty emerging markets, among which, several Asian markets (Indonesia, Korea, Malaysia, Philippines, Thailand) are included. They find that besides market risk, firm size, E/P ratio and turn over factors are significant in explaining a cross-section of stock returns. Among those Asian countries, the market beta has no explanatory power on most of the stock markets, only India, Malaysia and Thailand stock market have size effect. Chui and Wei (1998) conduct empirical tests on the robustness of the multifactor model in the Asian region. They examine the relationship between expected stock returns and market beta, size and B/M equity in five Asian emerging stock markets: Hong Kong, Korea, Malaysia, Taiwan, and Thailand. Their results suggest a weak relationship between average stock returns and the market beta for all five markets. But the book-to-market equity can explain the cross-sectional variation of expected returns in Hong Kong, Korea, and Malaysia, while the size effect is significant in all five markets except Taiwan. Drew (2003) compares the explanatory power of FF3F Model in Hong Kong, Korea, Malaysia and Philippines, and the author documents that size and value effects exist for all four markets but the multifactor model of FF provides a parsimonious description of the cross-section of returns for these Asian markets over the 1990s. Furthermore, Shum and Tang (2005) apply FF3F Model on three Asian emerging markets: HK, Singapore and Taiwan over the period July 1986 to December 1998, and they conclude that the model largely explains the variations in average returns when using the contemporaneous market factor, but the impact of size effect and value effect is very limited and insignificant in most cases. Sehgal et al. (2014) test the equity market anomalies for six emerging market including China, India, Indonesia, South Korea and South Africa. They find that there is size effect in India and both size and value effect in South Korea.

Connor and Sehgal (2001) find a pervasive influence of FF3F model on random stock returns in India from 1989 to 1998, however, the market factor alone cannot explain the cross-sectional stock returns. Sehgal and Balakrishnan (2013) re-examine the robustness of CAPM and FF3F model using data from 1996 to 2010, and results turn out that FF3F model does a better job in explaining the returns on most portfolios constructed based on firm size and B/M equity ratio. Ranjan Dash and Mahakud (2013) propose a multifactor model which include liquidity, market leverage, and momentum along with size and value factors to investigate the firm-specific anomaly effect and to identify market anomalies that account for the cross-sectional regularity in the Indian stock market. Though the anomaly effect is weak, their five-factor model is able to capture the B/M equity, liquidity, and medium-term momentum effect, and size, market leverage, and short-run momentum effect are found to be persistent in the Indian stock market. Based on the data of period Jun 2001 to Jun 2006, Jun 2004 to Jun 2009, Oct 1998 to Sep 2013, Jan1997 to Jun 2012 and Jan 1997 to Aug 2014, separately, Bahl (2006), Taneja (2010), Das (2015), Balakrishnan (2014) and Balakrishnan (2016)'s research continues to prove the existent of the size and value effect in the Indian stock market.

In other Asian emerging markets, Ferdian et al. (2011) find that market beta alone is not sufficient to describe the variation in average equity returns, but there exist size and value premium for Indonesian Shariah Stocks over the period September 2007 to September 2009. However, Sudiyatno and Irsad (2013) find no prove of size and value effects but a significant positive relationship between the risk premium and stock returns over the period 2007 to 2009 in Indonesia stock exchange. Amanda and Husodo (2014) explore FF3F Model along with liquidity in Indonesia from 2003 to 2013, and they conclude that there are market risk premium, size premium, value premium and liquidity risk premium which can explain the excess return in Indonesia.

Lau et al. (2002) examine the relationship between stock returns and beta, size, the earnings-to-price ratio, the cash flow-to-price ratio, the book-to-market equity ratio, and sales growth. And they proved the existence of anomalies in Singapore and Malaysia for the period June 1988 to December 1996. Drew and Veeraraghavan (2002) present evidence of the size and value premium for the case of the Malaysia. They report that the factors identified by FF explain the variation in stock returns in Malaysia and are not sample specific. The analysis was restricted to firms with available returns data from December 1992 to December 1999. Their findings clearly document evidence of a size and B/M equity effect that small and high B/M equity stocks generate higher returns than big and low B/M stocks in Malaysia. The results also show that the explanatory power of the variables is powerful throughout the sample period and not solely in January.

Lam (2002) investigates the relation between stock returns and size, leverage, B/M ratio, and earnings–price (E/P) ratio in Hong Kong stock market using FF approach. And he proves that market beta is unable to explain the average monthly returns on stocks listed in Hong Kong Stock Exchange over the period July 1984 to June 1997. But size, book-to-market equity, and E/P ratio seem able to capture the cross-sectional variation in average monthly returns over the period. Other two variables book and market leverages, are also able to capture the cross-sectional variation in average monthly returns. But their effects seem to be dominated by size, book-to-market equity, and E/P ratio, and considered to be redundant in explaining average returns when size, book-to-market equity, and E/P ratios are also considered. Ho et al. (2006) examine whether market beta, size and B/M ratio are priced under different market conditions on Hong Kong stock market, such as the up or down market. It is found that, for the whole market, size and B/M ratio were priced but not market beta. However, separate the whole market into up and down markets, there exists a significant systematic relation between market beta and stock returns. But size effect is insignificant in up markets, and B/M effect is negligible in down markets

Moreover, Homsud et al. (2009) prove the efficiency of FF3F model in The Stock Exchange of Thailand over the period July 2002 to May 2007 and they conclude that FF3F model can explain risk in stock returns better than the traditional CAPM. Phong and Hoang (2012) assess the application of FF3F Model in Vietnam's stock market from Jan 2007 to Dec 2011, and the results show that FF3F Model explaining average stock returns superior to CAPM.

In general, there are pervasive size and value effects while the market beta seems not able to explain cross-sectional stock returns on most Asian emerging markets. Thus, the FF3F

Model performs better than CAPM in explaining the anomalies of stock returns, especially size and value anomalies according to the researches mentioned above.

1.2.2.3 Empirical tests in Chinese stock market

As the biggest emerging market in Asian, Chinese stock market has attracted considerable attention, the cross-sectional relationship between firm-specific characteristics, such as firm size and B/M equity, and stock returns is also an intriguing issue for researchers. Previous studies identify several important factors in explaining stock returns in various stock markets around the world. There is limited literature that investigate the CNAS market in this respect until recent years (after 2010) and more researchers consider the special features of Chinese stock market, which we will precise in next section. This part will review the studies that apply the FF3F Model to Chinese mainland stock market returns.

Drew et al. (2003) use data of Shanghai Stock Exchange for the period 1993 to 2000, and test the multifactor approach to asset pricing in China considering the non-tradable and tradable market value. Their analysis suggest that market beta alone is not sufficient to explain the variation in the average stock returns, and small and growth firms generate superior returns than big and value firms, but value effect is not as pervasive as was found for the US portfolios and other international markets. In addition, the authors also conclude that there is no proof of seasonal effects, such as the January and/or Chinese New Year effect, which can determine the size and value effects. However, they only run the one-stage time series regressions using mimic portfolios based on size and book-to-market equity, no cross-sectional pricing analysis was conducted.

Wang and Xu (2004) investigate FF3F Model on CNAS stock market including both the Shanghai and Shenzhen A-share stock markets for the sample period July 1996 to June 2002. Firm size is proved to explain the cross-sectional differences in average stock returns, but contrary to the findings on U.S. market, their results showed the B/M ratio had no effect on the Chinese stock markets.

Both Eun and Huang (2007) and Wang and Di Iorio (2007) explore the cross-sectional relationship of average stock returns and several Chinese firms-specific characteristics in the CNAS stock market and both find that market beta lacks the explanatory power even when the beta effect is examined respectively. Wang and Di Iorio (2007) propose that the absence of a market beta effect may be attributed to some specific market characteristics in the A-share market, such as government intervention, irrational behavior of individual investors, and the prohibition of short sales (reference to Kang et al. (2002), Hu (1999) and Wang (2004)). However, their results suggest the existence of value effects in addition to size effect over their research periods, which is contrary to the findings of Wang and Xu (2004).

Rutledge et al. (2008) investigate whether there is a size effect in case of bull and bear markets in Chinse stock market over a six-year period from 1998 to 2003. And they find small firms have significantly greater positive excess returns than large firms during the bull market, however, small firms have significantly greater negative returns (using total market value), or no significant difference in returns (using float market value) during the bear market period.

Wong et al. (2006) and Morelli (2012) both focus on the A-share stock market of Shanghai Stock Exchange in China. The former explores the cross-sectional stock return behavior and estimate the beta, size and value effects over the period 1993 to 2002, results show that smaller firms and value stocks perform better. Systematic risk is negatively significant in down markets. The latter explores the cross-sectional relationship between security returns and beta, size and book-to-market equity, and there is no proof of an unconditional relationship between market beta and returns. However, a conditional relationship is found when the data is split into up and down markets, the relationship holds even in the presence of size and book-to-market equity. Both size and book-to-market equity are found to display both an unconditional and conditional relationship with stock returns.

Researches are applied on Chinese stock market during recent years, especially after 2010. Xuanjuan Chen et al. (2010) take 18 firm-specific variables which are demonstrated to predict cross-sectional stock returns in U.S and examine their relationship with stock returns in Chinese stock market over the period 1995 to 2007. But only five variables are able to predict stock returns (B/M equity, assets growth, and illiquidity, etc.), and not as in U.S. market, in multivariate regression tests few variables succeed in multivariate regression tests.

Contradict with most of the existing literature that there exist size and value effect across the returns of Chinese stock market[7], Wu (2011) apply FF3F model on CNAS markets: Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), separately, June 1992 to April 2009 for SSE and February 1996 to April 2009 for SZSE. The results of CSRs suggest that market beta has no explanatory power when examined alone or with other factors, and there is evidence of value effect on SSE but no size effect was found. Finally, the author has the conclusion that the model works better in SSE than in SZSE. Contradictorily, Chen et al. (2015) find a strong size effect but no value effect cross returns based on the data period July 1997 to December 2013 in Chinese stock market, the results, which is consistent with Wang and Xu (2004).

[7] Eun and Huang (2007), Wang and Di Iorio (2007), Cakici et al. (2015) and Gan et al. (2013).

It is noteworthy that more and more researchers take the special features of Chinese stock market into consideration. For instance, Chen (2004)[8] examines the performance of the Fama-French three-factor model for CNASs. The author sorts stocks by their tradable shares' market value into three size groups using breakpoints at the 30% and 70% percentiles. The portfolio returns are value-weighted by the tradable shares' market value. Mao et al. (2008)[9] apply the FF3F Model to study the long-run return performance after Chinese listed firms completed rights offering. To construct the three factors, they also sort stocks into two size groups by their tradable shares' market value. Liao and Shen (2008)[10] use FF3F Model to examine stock price reaction to Chinese listed firms' completion of the split-share structure reform that was initiated in April 2005. To construct the size factor, they separate small and large stocks by the median of their tradable shares' market value, which is defined as the number of tradable shares at the beginning of each year multiplied by share price. To construct the value factor, they use the net assets per share divided by share price as the B/M ratio because of the market segmentation in China. The portfolio returns are value-weighted by the tradable shares' market value, which implicitly assumes that the portfolios include only tradable shares. In order to examine the explanatory power of the FF3F Model on Chinese bond returns, Liu and Yang (2010)[11] sort stocks by their price-to-book ratio into three groups, and the portfolio returns are value-weighted by the total market value; to construct the size factor, they sort stocks by their total market value into two groups. The results show that two factors, SMB and HML, do not contribute significantly to explaining Chinese bond returns.

Zhang and Xu (2013) provide an empirical evidence of to what extent the three factors explain the variation in Chinese stock returns and identify some pitfalls that arise in the application of the three-factor model to Chinese stock returns. They summarize three special features of Chinese stock market that potentially affect the three factors considerably which also have the influence to the explanatory power of FF three-factor model. In addition to the tradable and non-tradable shares and market segmentation in Chinese stock market, they also take into account that whether Small Medium Enterprise

[8] Chen, Zhanhui. (2004), '*Cross-sectional Variations and Three Factors Asset Pricing Model: Empirical Evidence from China A-Share Market*', Chinese Journal of Management Science 6: 13-18 (in Chinese).

[9] Mao, X-Y., Chen, M-G. and Yang, Y-H. (2008), '*Long-run Return Performance following Listed Rights Issue: Based on the Improved Three-factor Model*', Journal of Financial Research 5: 114-129 (in Chinese).

[10] Liao, L. and Shen, H-B. (2008), '*Fama-French Three Factors Model and the Effect of the Split-share Structure Reform*', The Journal of Quantitative and Technical Economics 9: 117-125 (in Chinese)

[11] Liu, G-M. and Yang, C. (2010), '*Application of Fama-French Multi-Factor Model in China's Bond Market during Recent Financial Crisis*', Journal of Zhejiang University (Science Edition) 4: 396-400 (in Chinese).

Board (SME) and the Growth Enterprise Board (GEB) listed firms should be excluded in determining the breakpoints for the size factor. They experiment with different ways of constructing the three factors in order to evaluate the effect of these special features in China, the results turn out to be that the formation of the three factors can have a big impact in empirical studies applying the FF3F Model to Chinese stock market. Overall, FF3F Model can explain more than 93% of the variation in the portfolio returns on CNASs for the period of 1996 to 2013, and it does not affect the explanatory power of FF3F model whether or not the SME and GEB stocks are included to determine the portfolio breakpoints. The explanatory power of the three-factor model is higher when the market portfolio includes only tradable shares than when the market portfolio includes both non-tradable and tradable shares, and when the book-to-price ratio (B/P) are used instead of the book-to-market ratio.

Though there is less research in Chinese stock market comparing to U.S. and other developed stock markets, there is time-series literature provide evidence that size or value (or both) effect(s) on Chinese stock market but the market beta seems not have explanatory power in explaining the cross-sectional stock returns in China. What's more, considering the special features of Chinese stock market seems to be the right direction to apply the FF3F Model to Chinese stock market as the literature documented, since the explanatory power of FF3F Model has clearly improved.

1.2.3 Profitability and investment factors and Fama-French Five-Factor Model

Cooper and Maio (2016) state that "*The investment anomaly can be broadly classified as a pattern in which stocks of firms that invest more exhibit lower average returns than the stocks of firms that invest less*", and "*the investment anomaly can be broadly classified as a pattern in which stocks of firms that invest more exhibit lower average returns than the stocks of firms that invest less*".

Sloan (1996) is the first who document that accruals are negatively related to future profitability and that higher accruals predict lower stock returns. Following, an extensive literature initiated by Sloan (1996), such as Chan et al. (2006) also indicate that accruals are reliably and negatively related to future stock returns (See also Xie (2001), Richardson et al. (2005), and Richardson et al. (2006)). Novy-Marx (2013) uncovers a positive relationship between profitable firms and expected returns that profitable firms earn significantly higher average returns than unprofitable firms. Haugen and Baker (1996b) and Cohen et al. (2002) find that controlling for B/M, average returns are positively related to profitability. Fairfield et al. (2003) find that the well-documented accrual anomaly extends to growth in long-term net operating assets, thus the accrual anomaly documented in Sloan (1996) is a subset of a larger anomaly with respect to a general market mispricing of growth in net operating assets.

Working within the confines of a valuation equation, Abarbanell and Bushee (1998), Frankel and Lee (1998), Dechow et al. (2000), combine analyst' forecasts of earnings with assumptions about future investment to estimate expected stock returns. General results indicate that higher expected net cash flows (expected profitability minus expected investment) relative to current market value forecast higher stock returns.

Titman et al. (2004) show that firms which increase capital investment tend to have future negative risk-adjusted returns; and a similar conclusion of a negative relation between average returns and investment is obtained by Richardson and Sloan (2003). Both Anderson and GARCIA-FEIJÓO (2006) and Cooper et al. (2008) find that firm-level investment growth is a robustly significant predictor of the cross-section stock returns, furthermore, the former propose that the investment anomaly appears to contain information similar to that of the B/M ratio. Fama and French (2008) investigate the anomalies which including the asset growth and profitability, and they provide evidence that higher profitability tends to be associated with abnormally high returns among profitable firms.

By applying a standard q-theory, Xing (2008a) constructs an investment growth factor, defined as the difference in returns between low-investment stocks and high-investment stocks. The author finds that the investment factor contains information similar to the FF (1993) value factor HML, and can explain the value effect about as well as HML. Similarly, Lyandres et al. (2008) construct the same investment factor as Xing (2008) and their results indicate that the investment factor earns a significantly positive average return.

In the paper of Fama and French (2006), they have already studied for the three variables, B/M ratio, profitability, and investment effects, which are related to expected stock returns according to dividend discount model and the valuation equation. And they confirm the implies of valuation theory that high rates of investment are related to low expected returns when controlling B/M ratio and profitability, while controlling two other variables, high profitable stocks have higher expected stock returns. Supporting FF valuation perception, Aharoni et al. (2013) find a positive relation between expected profitability and returns, and crucially a negative relation between expected investment and returns. They emphasize that "*measuring investment at the firm level rather than per share level is the key to empirically understanding the simultaneous relation between expected returns, B/M, expected profitability, and expected investment*".

Especially, Hou et al. (2014) examine nearly 80 anomalies in the literature from January 1972 to December 2012 on U.S. market based on q-theory, but about one-half of the anomalies seems exaggerated their explaining power for average stock returns. They come to a conclusion that a four-factor model which includes the market factor, size factor, profitability factor and investment factor explains the cross-sectional average stock returns to a large extent, and outperforms the FF3F model and Carhart (1997) four-factor models.

Inspired by recently research that give evidence to the remarkable existence of profitability and investment effects, based on the dividend discount model (equation (1.3)), Fama and French (2015a) propose a five-factor model contains the market factor and factors related to size, book-to-market equity ratio, profitability and investment and test the performance of the five-factor model for the U.S. market using the data from July 1963 to December 2013. (Data period July 1963-December 2013). They use three sets of factors[12] in order to examine whether the specifics of factor construction do have an important impact on the results of the test of asset pricing models. Furthermore, they show GRS statistic of Gibbons et al. (1989) to test whether the intercepts are indistinguishable from zero in the regressions of the portfolios' excess returns on the models' factor returns so that to distinguish whether a model can completely capture expected returns.

The results show that the factors from the 2x3, 2x2 and 2x2x2x2 sorts obtain much the same results in testing of a given model, and although the GRS tests[13] indicate that all the models are incomplete descriptions of expected average returns, the FF5F model outperforms FF3F model by adding profitability and investment factors. As FF themselves say, "*Despite rejection on the GRS test, the five-factor model performs well: unexplained average returns for individual portfolios are almost all close to zero*".

Meanwhile, FF find that when the profitability and investment factors are added into FF3F model, the value factor HML seems to become redundant in explaining average expected returns. Thus, they draw a conclusion that the value factor HML is a redundant factor for

[12] The three sets of factors are: 2x3 sorts on Size and B/M, or Size and OP, or Size and Inv; 2x2 sorts on Size and B/M, or Size and OP, or Size and Inv; and 2x2x2x2 sorts on Size, B/M, OP and Inv (see details in Fama and French, 2014). 2x3 sorts on Size and B/M is that the size and value factors are independently sort stocks into two size groups and three B/M groups, and construct the size factor SMB and value factor HML as of FF3F model; the 2x3 sorts on Size and OP or Size and Inv are the same as Size and B/M except the sort for B/M groups are replaced by operating profitability or investment. 2x2 sorts method is similar as 2x3 sorts except that the stocks are all independently sorted into two groups. In 2x2x2x2 sorts is that the size factor SMB equal weights high and low B/M, robust and weak OP, and conservative and aggressive Inv portfolio returns.

[13] The GRS test examine whether an asset pricing model completely captures expected returns. If the five-factor model can explain all cross-sectional variation in expected stock returns, then the intercept will be indistinguishable from zero in a regression of an asset's excess returns on the model's factor returns.

describing average returns in FF5F model, which is consistent with the previous findings of Anderson and GARCIA-FEIJÓO (2006) and Xing (2008a). They explain this outcome is because "*the average HML return is captured by the exposures of HML to other factors (market factor, SMB, HML and especially RMW and CMA)*".

FF's (2015a) results suggest that a five-factor model performs better than their FF3F Model. But the five-factor model fails to capture low average returns on small stocks with high investment and low profitability. They also show that the model's performance is not affected by the way the factors are calculated. With two additional factors, their results also suggest that the value factor (HML) becomes redundant.

There is not much research on FF Five-Factor model out of America. FF (2015b) proceed the international tests of FF5F model in North America, Europe, Japan, and Asia-Pacific. Expected stock returns increase with the B/M ratio and profitability and decrease with investment for North America, Europe, and Asia Pacific, however, the average stock returns show little relation to profitability or investment factors. On Brazilian market, Martinsa and Eid Jr (2015) test the performance of FF5F model during the period January 2002- December 2012 and find that FF5F Model performs better than their previous work in the three-factor model. The market factor, SMB, and HML capture most of the variation in average returns in the TSR, however, the two new factors RMW and CMA have shown less explanatory power. Chiah et al. (2015) investigate the FF5F Model on Australia market, and they find that the profitability and investment factors have significantly positive premium. FF5F Model is proved to be able to explain average stock returns better than FF3F Model in Australia, in contrary to FF (2015a) results, the value factor (HML) remains its explanatory power in the presence of the investment and profitability factors.

To the best of our knowledge, there is no such a work on Chinese stock market so far. In next section, we will present the empirical results that we apply FF5F Model on CNAS stock market.

1.3 Introduction of Chinese stock market

1.3.1 Background of Chinese stock market

In the past 30 years, China experienced extraordinary economic growth and has become an increasingly important member of the global economy. One of the critical economic reforms was the introduction and the development of the stock markets. Still young and immature, the Chinese stock markets have grown rapidly and now become the second largest in terms of market capitalization.

On Chinese stock market, there are three kinds of stocks: A-share stocks, B-share 'stocks, and H-share stocks. The 'A-shares' do not refer to the 'class' of common or preferred stocks as usual, it refers to shares that are purchased and traded on the SSE and SZSE, which are two membership institutions governed directly by the China Securities Regulatory Commission (CSRC). These companies are incorporated in mainland China and their shares are denominated in the local currency Chinese yuan, or RenMinBi (RMB). For individual investors, these stocks of the A-share market are strictly off limits to non-Chinese investors. Meanwhile, some Chinese companies are listed in Shanghai and Shenzhen, but their shares trade in U.S. dollars. These stocks, known as 'B-Share', were designed to give Chinese companies a way to raise capital from overseas. 'B-Shares' also allow foreign (non-Chinese) investors to invest in this market without the restrictions associated with 'A-shares'. 'H-shares' are also Chinese companies, but these securities are traded on the Hong Kong Stock Exchange rather than on the mainland, and they are priced in Hong Kong dollars.

The Chinese stock market is a young market with relative short history, and it has grown and expanded rapidly since the establishment of Shanghai stock exchange (SSE) on November 26th, 1990 - in operation on December 19th of the same year and the other stock exchange- Shenzhen stock exchange(SZSE) on December 1st, 1990 (opened on July 3rd, 1991). The total listed firms on A-share stock market increase rapidly from 14 of the year 1991 to more than 1000 of the year 2001, and more than 2500 until now (in SSE and in SZSE). This rapid growth has attracted considerable academic interests; many studies have examined the ability of FF3F model to predict the stock price movements of Chinese stock.

Figure 1.1[14] shows the performance of both Shanghai Stock Exchange A-Share (SHASHR) Index and Shenzhen Stock Exchange A-Share (SZASHR) Index from 1992 to 2015. It contains two parts, index point (white for SHASHR Index and green for SZASHR) and volume (grey for SHASHR and rose red for SZASHR). SHASHR Index has averaged 1921.11 index points from 1992 until 2015, reaching the highest 6395.76 index points in October of 2007 and a record low of 293.75 index points in January of 1992. SZASHR Index reaches the record high also in 2007 (2015 not included), a record low of 95.26 in July 1994, and has averaged 681.16 index points from 1991-2015. Both indexes have the volume increased before 2007 and change unstable after, until 2014 and 2015, both indexes have a remarkable growth. Figure 1.2 shows the performance of both SHASHR Index and NYSE Composite (NYA) Index in U.S., in the upper part, the white line is SHASHR Index

[14] Source: Bloomberg Finance L.P.

Figure 1.1 SHASHR Index and SZASHR Index (1992-2015)

This figure shows the performance of both Shanghai Stock Exchange A-Share (SHASHR) Index and Shenzhen Stock Exchange A-Share (SZASHR) Index from 1992 to 2015. The upper part is the index point, white for SHASHR Index and green for SZASHR Index; the nether part is the volume, grey for SHASHR Index and rose red for SZASHR Index.

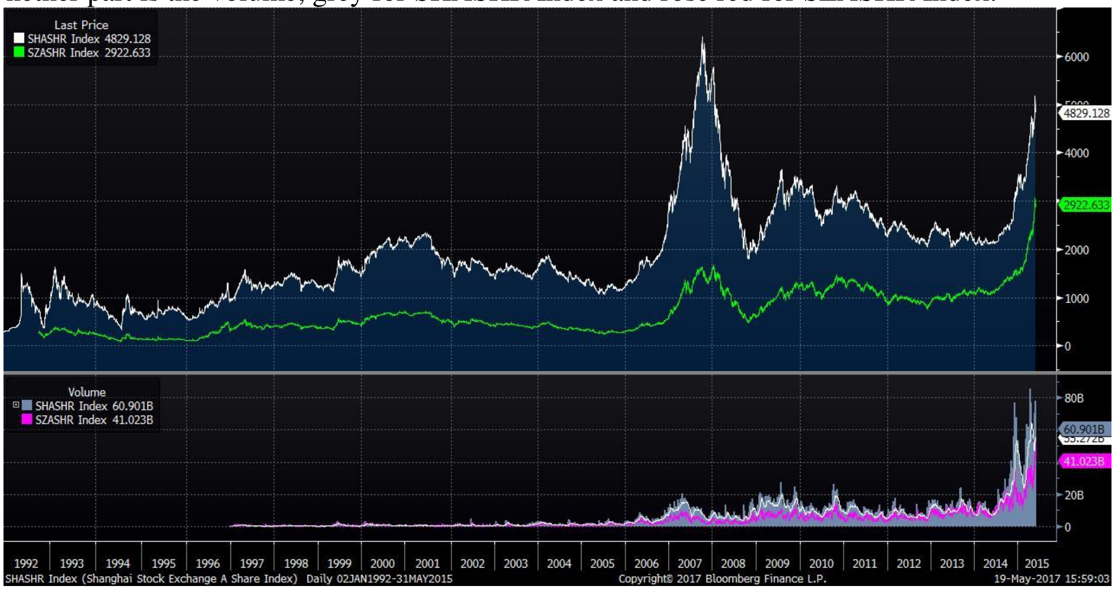
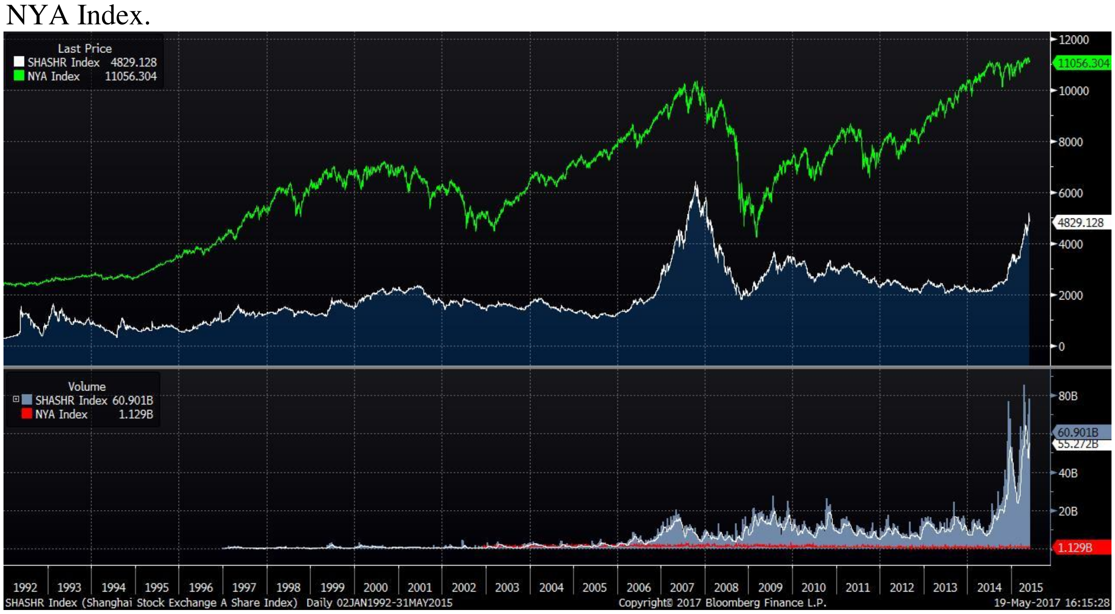


Figure 1.2 SHASHR Index and NYSE Composite Index (1992-2015)

This figure shows the performance of both SHASHR Index and NYSE Composite (NYA) Index from 1992 to 2015. The upper part is the index point, white for SHASHR Index and green for NYA Index; the nether part is the volume, grey for SHASHR Index and red for NYA Index.



while the green one is NYA Index. Thought the index price of NYA Index is much higher than that of SHASHR Index, the trends of both indexes are much similar.

Table 1.1 shows the summary of Chinese stock market, the annual total listed firms on the whole stock market and listed firms respectively on SSE and SZSE from 1990-2014, listed stocks of A-share stock market, total market capitalization (whole stock market, A-share

Table 1.1 Summary of Chinese stock market 1990-2014[15]

The first column is the year from 1990 to 2014, and total listed firms, listed firms on SSE (denoted as SSE) and SZSE (denoted as SZSE), listed stocks of A-share (Stocks of A), and total market capitalization (Total market cap) of whole Chinese stock market, A-share market (A) and B-share market (B) are represented in the following columns. The last column is the percentage of B-share value in total market capitalization (B value in total). The unit of total market capitalization is 100 million yuan. The symbol '-' indicate the data that we fail to obtain.

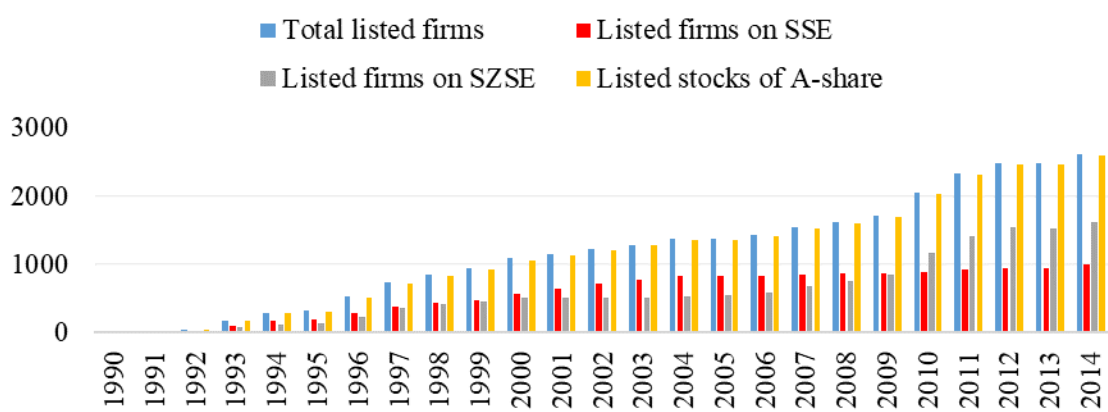
Year	Total listed firms	SSE	SZSE	Stocks of A	Total market cap	Total market cap of A	Total market cap of B	B value in total (%)
1990	10	8	2	-	-	-	-	-
1991	14	8	6	-	-	-	-	-
1992	53	29	24	53	1048	978	70	6.68%
1993	183	106	77	177	3531	3319	212	6.00%
1994	291	171	120	287	3691	3516	175	4.74%
1995	323	188	135	311	3474	3311	164	4.72%
1996	530	293	237	514	9842	9449	394	4.00%
1997	745	383	362	720	17529	17154	375	2.14%
1998	851	438	413	825	19506	19299	206	1.06%
1999	949	484	465	922	26471	26168	304	1.15%
2000	1088	572	516	1060	48091	47456	635	1.32%
2001	1160	646	514	1140	43522	42246	1277	2.93%
2002	1224	715	509	1213	38329	37527	803	2.10%
2003	1287	780	507	1277	42458	41520	937	2.21%
2004	1377	837	540	1363	37056	36309	746	2.01%
2005	1381	834	547	1358	32430	31811	620	1.91%
2006	1434	842	592	1411	89404	88114	1290	1.44%
2007	1550	860	690	1527	327141	324588	2553	0.78%
2008	1625	864	761	1602	121366	120567	800	0.66%
2009	1718	870	848	1696	243939	242127	1812	0.74%
2010	2063	894	1169	2041	265423	263221	2202	0.83%
2011	2342	931	1411	2320	214758	213310	1448	0.67%
2012	2494	954	1540	2472	230358	228775	1582	0.69%
2013	2489	953	1536	2468	239077	237403	1674	0.70%
2014	2613	995	1618	2592	372547	370823	1724	0.46%

[15] Source: http://www.stats.gov.cn/

stock market and B-share stock market, respectively) and the percent of B-share market capitalization in total market capitalization from 1992 to 2014. Figure 1.3, Figure 1.4 are created to visualized Table 1.1. Figure 1.3 shows the total listed firms and that of SSE and SZSE from 1990 to 2014, listed stocks of A-share stock market are also presented. Figure 1.4 represents the total market capitalization of the whole stock market and also respectively of A-share stock market and B-share stock market from 1992 to 2014.

From Table 1.1 and the figures 1.3 and 1.4, it is obvious that the Chinese stock market has undergone a dramatic growth since its establishment in 1990. The total listed firms increase sharply during 25 years (from 10 total listed firms in 1990 to 1088 in 2000, and 2613 total listed firms in the year 2014), and total market capitalization from RMB 104.8 billion (year 1992) to 37 254.7 billion (year 2014). The total listed stocks in A-share stock market increased from 53 (year 1992) to 2592 (year 2014) with a combined market capitalization of RMB 97.8 billion in 1992 to 37 082.3 billion in 2014.

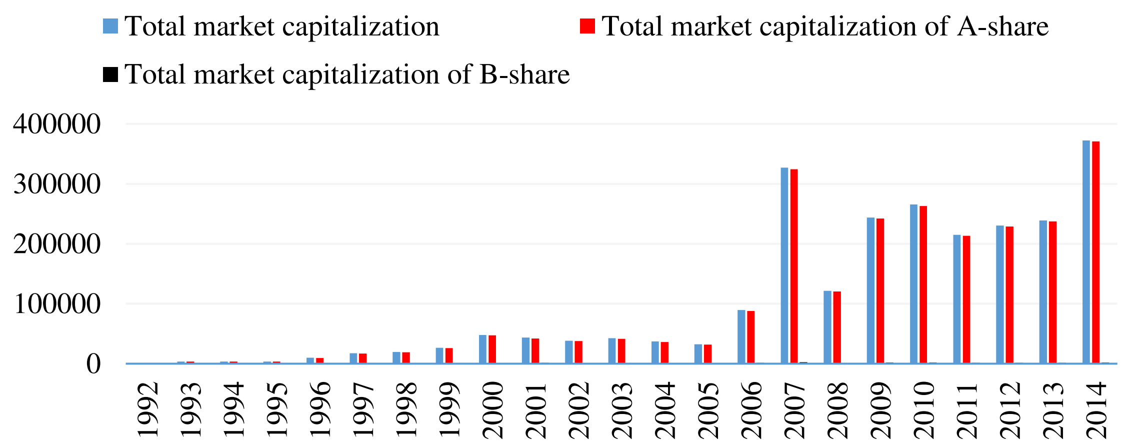
Figure 1.3 Total listed firms and that of SSE and SZSE, listed stocks of A-share stock market (1990-2014)



Much of the literature[16] that studies Chinese stock market has focused on the segmentation of the market and mispricing between A shares, denominated in domestic currency, and B shares, traded in foreign currency. However, this anomaly has been significantly reduced following the opening of the B market to domestic investors in 2001[17]. The percentages of B-share market capitalization in total market capitalization show that A-share account for the vast majority of the total market capitalization (more than 99% after 2006), and B-shares account for only a very small part of the total market capitalization after 2001 and even less

[16]See Sun and Tong (2000), Chen et al. (2001), Fung et al. (2000) and Fernald and Rogers (2002).
[17] Ahlgren et al. (2009)

Figure 1.4 Total market capitalization and that of A-share and B-share stock market (unit:100 million yuan; 1992-2014)



than 1% from 2007 (2.93% of year 2001, 0.46% of year 2014). Our research will focus only on CNAS stock market.

1.3.2 Special features of Chinese stock market

The emerging empirical literature suggests that Chinese market has some special features, and it is inevitable to consider those special features if researchers want to have more accurate results in China. Chen (2004), Mao et al. (2008), Zhang and Xu (2013), Liu and Yang (2010) and Hung et al. (2015) all do their research considering one or several special features on Chinese stock market. We summarize three primary features which are also most frequently employed by literature.

- Firstly, it is well known that China, like many markets in the Asian region, has substantial holdings of non-traded shares which mean that these shares are not effectively valued. Before April 2005, listed companies had two kinds of shares outstanding which are tradable shares and non-tradable shares. Non-tradable shares were held by government agencies or government-related enterprises and were non-tradable in the public market. The Chinese government started the share-structure reform in April 2005 to legally convert non-tradable shares to tradable shares. Almost all Chinese listed companies completed the reform by the end of 2006. Using only tradable shares or all shares to value weight stock returns is necessary to investigate.

- Another important special feature is the segmentation of Chinese stock market, more than 170 Chinese listed firms have issued multiple class shares which have the same cash flow and voting rights but are traded in different markets. Some of them have A-shares and B-shares, some have A-shares and H-shares and others have the A-shares and shares in other foreign markets. Since these shares share the same cash flow and voting rights, they usually have the same claim on the firm's book value of equity. Our research focus only the CNAS stock market, in order to obtain the book-to-market equity ratio per A-share of a company with multiple class shares, it is incorrect to divide the firm's total book value equity from its balance sheet by the total market value. Instead, the correct way is to calculate the book value of equity per share divided by the A-share price.

- Thirdly, China has two main boards for the firms to go public, the SSE and the SZSE. In addition, the SME and the GEB were set up in May 2004 and October 2009, respectively, and both are hosted by the Shenzhen Stock Exchange. Fama and French use NYSE-listed firms to determine the breakpoints between small and big firms in order to avoid the overwhelming influence of the large number of small NASDAQ firms. Therefore, whether SME and GEB listed firms should be excluded in determining the breakpoints for the size factor in China need to be examined. Zhang and Xu (2013) conclude in their paper that the SME and GEB stocks are included or excluded from the sample to divide firms into size groups do not have a distinct difference.

Based on these special features of Chinese stock market, Zhang and Xu (2013) construct FF three factors and process the regressions separately with and without these special features. They come to the conclusions that the performance of FF3F Model is better when the non-tradable shares are excluded from the sample and when the book-to-price ratio (B/P) are used instead of the B/M ratio.

On account of the special features of Chinese stock market study in literature, we construct value-weighted stocks by their tradable shares, use B/P ratio instead of B/M ratio, and construct of size factor by the total market capitalization including SME and GEB in our following research.

1.4 Empirical Analysis and Results of FF3F Model

1.4.1 Data and methodology

1.4.1.1 Data

All the firms on CNAS stock market, excluding financial firms[18] and firms with negative market-to-book values, are collected from Shanghai A-Share Index and Shenzhen A-Share Index. In addition, a firm is eliminated if the relevant information is missing in a particular month or period, and the obvious errors are corrected manually.

For the period of July 2004 to May 2015 (131 months), monthly index prices and stock prices are obtained from Bloomberg, so as to their market capitalization, book value per share, total shares outstanding and listed shares outstanding. Furthermore, risk-free rate (RF rate) is a typically proxy for the return on a one-month Treasury bill. But in China, the one-month Treasury bill has never been issued until February 2007. To keep it consistent with our sample period, we replace it with 'Three-Month Treasury Bill Rate (3M T-Bill Rate)' and the one-month risk-free rate is then equal to the 3M T-Bill Rate divided by three.

Considering the special features of Chinese stock market, and as already demonstrated in the section 1.3.2 that the best performance of three-factor model is achieved when the three factors are constructed by using the market portfolio that includes only tradable shares; using the total market value to determine size breakpoints; and when the B/P ratio is used instead of the B/M equity ratio.

For each stock:

- The stock return is defined as the logarithm of the difference of monthly price.
- The firm's size is defined as the natural logarithm of the market capitalization in local currency Chinese 'yuan' (RMB).
- Instead of B/M equity ratio, B/P ratio is calculated as a firm's book value per share divided by its price.
- To calculate the value-weighted returns, the tradable market value of equity instead of the total market value of equity is used, the tradable market value of equity

[18] The financial firms are excluded because their high leverage which is normal for these firms maybe does not have the same meaning for non-financial firms, where high leverage more likely presents high distress risk.

equals to the stock price of each month times the number of tradable shares (Listed shares outstanding).

1.4.1.2 Construction of Fama-French portfolios on Chinese market

We follow FF method as demonstrated in section 1.2.1 and construct the 6 Size-B/P portfolios on Chinese stock market, SL, SM, SH, BL, BM, and BH, to form the size factor SMB, at the end of June of each year *t*, all the stocks are sorted into two size groups, Small and Big, the breakpoint is the median total market capitalization including SME and GEB listed firms. For the value factor HML, we sort by the B/P ratio instead of B/M ratio at the end of each December of year *t-1* into three groups: Low, Medium and High. The breakpoints are the 30th and 70th A-shares percentiles. Finally, the intersection of these six groups makes the six portfolios, which remain the same from July of year *t* to June of year *t+1*, and the portfolios are reformed in July of year *t+1*.

The "market" portfolio return series, which covers both the Shanghai and Shenzhen exchanges, is not readily available. We first compute the monthly returns of Shanghai and Shenzhen composite A-share indexes separately, then compute the value-weighted average of the returns using the relative (aggregate) market values of the two exchanges observed at the end of each month as weights. The weighted average market returns thus obtained are used as our proxy for market returns.

Then the market factor is the excess market return which is computed as the difference between the value-weighted returns of all A-shares and the RF rate. The SMB factor is then the difference between the simple average of the monthly returns of the three small-size portfolios (SL, SM, and SH) and the simple average of monthly returns of the three big-size portfolios (BL, BM, and BH). Similarly, HML is equal to the simple average monthly return of the two portfolios with high book-to-market equity (SH and BH) minus which of the two portfolios with low book-to-market equity (SL and BL)

Most literature including FF themselves construct 25 portfolios which are the intersection of five portfolios formed on size (Small, 2, 3, 4, and Big) and five portfolios formed on B/M ratio (Low, 2, 3, 4, and High). The 25 Size-B/P portfolios are formed much like the six Size-B/P portfolios discussed above, we firstly sort firms into five size groups at the end of June of year *t*, the breakpoints are all the A-share market equity quintiles. Then independently, we sort firms into five B/P ratio groups at the end of year *t-1*, for which the breakpoints are all A-shares quintile. Similarly, the portfolios remain unchanged from July of year t to June of year *t+1*, and the portfolios are reconstructed at June of year *t+1*.

Thus, to be included in our data set, a stock must have market equity data for December of *t-1* and June of *t*, and (positive) price data for *t-1*, in addition, firms must have monthly returns for at least 24 out of 131 months between July 2004 to May 2014. Ultimately, the total number of stocks which meet our selecting criteria on A-share market is 2267.

1.4.2 Empirical results on Chinese A-share stock market

1.4.2.1 Summary statistics

Table 1.2 shows the annual average available number of firms which have the data of market capitalization, B/M ratio, and tradable market value each year without the financial firms and negative B/M firms. The data are not so satisfactory before 2003 after the non-financial firms and firms with negative B/M ratio are eliminated from the sample. The available number of B/M ratio are always less than that of size, especially before 2003, such as the available number of firm size is 895 in the year 2001 while the number of firm B/M ratio is only 15.

Table 1.2 Annual average available number of firms that have required data (2001-2014)

This table represents the annual average number of firms which have available data of market capitalization, book-to-market equity ratio and tradable market value. The first column is the year from 2001 to 2014, the following columns are the available amount of data of market capitalization, B/P ratio and tradable market value of A-share stock market, separately. The symbol '-' indicate the data that is not available.

Year	Market capitalization	B/P ratio	Tradable market value
2001	895	15	-
2002	950	476	-
2003	1013	709	352
2004	1105	929	1128
2005	1158	1020	1119
2006	1175	1008	1159
2007	1254	1106	1255
2008	1352	1218	1360
2009	1408	1286	1478
2010	1662	1500	1786
2011	1977	1846	2058
2012	2189	2069	2204
2013	2248	2110	2172
2014	2224	2040	2113

Besides, the number of firms which have the available tradable market value is less than 400 before 2004. To reduce the bias of the regression results, we choose the time interval July 2004 to May 2015 and construct three factors during 131 months.

To construct the three factors, the monthly price of the market portfolios (SSE A-Share Index and SZSE A-Share Index) and the eligible stocks, total market capitalization, tradable market value, and book value per share of CNAS market are obtained from Bloomberg. The 3-month Treasury Bond Trading Rate, which downloaded from Bloomberg as well, and the monthly risk-free rate is the 3M T-Bill Rate divided by three.

Table 1.3 reports the statistic description of FF six Size-B/P ratio portfolios. The five parts: annual average of firm size, annual average of B/P ratio, average of annual percent of market value in portfolio, average of annual number of firms in portfolios and average excess returns are represented in Panel A, B, C, D and E respectively. Firstly, across the two size groups, high B/P ratio portfolios have relatively bigger size, and then across the three B/P ratio groups, big size portfolios have relatively higher B/P ratio than small size portfolios. In Panel C, the big size portfolios contribute about 86.30% in total with the nearly number of firms as the small size portfolios (733 firms for small size portfolios and 732 firms for big size portfolios).

Table 1.3 Descriptive statistic of Fama-French six value-weighted Size-B/P portfolios (period: July 2004- May 2015)

This table reports the statistic description of six Size-B/P portfolios (SL, SM, SH, BL, BM and BH), their annually average of firm size and B/P ratio are presented in Panel A and Panel B separately, Panel C is annual average percentage of market value in portfolios, Panel D is the annual average of firm numbers and Panel E is the average excess return of the six portfolios. Across the columns are the two size groups (Small and Big) and across the rows are three B/P groups (Low, Medium and High). The unit of market value is 100 million 'yuan'.

	Book-to-Price (B/P) ratio					
	L	M	H	L	M	H
	Panel A: Average of annual firm size			**Panel B: Average of annual B/P ratio**		
S	2171	2216	2351	0.2105	0.3680	0.5695
B	11955	14265	16373	0.2294	0.3820	0.6358
	Panel C: Average of annual percent of market value in portfolio			**Panel D: Average of annual number of firms in portfolio**		
S	4.39%	4.54%	4.78%	190	316	227
B	24.74%	30.73%	30.83%	249	271	212
	Panel E: Average excess returns					
S	0.0236	0.0251	0.0244			
B	0.0161	0.0142	0.0123			

The average excess returns in Panel E are consistent with FF, in which big size portfolios tend to have lower excess returns than small size portfolios. However, the average excess returns across the B/P ratio seem not to have a clear tendency, only in the big size groups, the excess returns decrease with B/P ratio, which is opposite to U.S. stock market.

In Table 1.4, Panel A displays the summary statistics of FF three factors (excess market return, SMB and HML) on CNAS stock market. Panel B and Panel C shows the correlation coefficients among dependent variables (FF three factors) and correlation coefficients between independent variables (excess returns of six Size-B/P portfolios) and dependent variables. Panel B indicates that the correlation coefficients between market beta and size factor SMB is 0.0014, and between the market factor and value factor HML is 0.1857, which are both low. The correlation coefficients between SMB and HML (-0.3224) indicates that size factor and value factor are negatively correlated. In Panel C, all the six portfolios and market factor are positively highly correlated. Small size portfolios are all

Table 1.4 Summary statistics of Fama-French three factors and correlation coefficients among variables (July 2004- May 2015)

Panel A is the summary statistics of FF three factors: the excess market return, Rm-Rf; the size factor SMB and the value factor HML. Panel B is the correlation coefficients among FF three factors, and Panel C is the correlation coefficients between excess returns of six Size-B/P portfolios and FF three factors.

Panel A: Summary statistics of Fama-French three factors			
	$R_{M,t} - R_f$	SMB	HML
Mean	-0.0006	0.0102	-0.0015
Standard Error	0.0077	0.0035	0.0028
Median	0.0051	0.0124	-0.0046
S.D.	0.0884	0.0403	0.0316
Sample Variance	0.0078	0.0016	0.0010
Kurtosis	1.1271	2.2564	4.5290
Skewness	-0.6384	-0.6685	0.4895
Panel B: Correlation coefficients among Fama-French three factors			
Rm-Rf	1		
SMB	0.0014	1	
HML	0.1857	-0.3224	1
Panel C: Correlation coefficients between dependent variables and independent variables			
SL-Rf	0.8037	0.5342	-0.0460
SM-Rf	0.8233	0.4989	-0.0024
SH-Rf	0.8274	0.4674	0.1130
BL-Rf	0.8990	0.1646	-0.0951
BM-Rf	0.9320	0.1270	0.1372
BH-Rf	0.9084	-0.0137	0.4570

relatively highly correlated with size factor SMB (0.5342, 0.4989 and 0.4674), while the correlation coefficients between big size portfolios and SMB are low (0.1646, 0.1270 and -0.0137), all the six portfolios are positively related with size factor except the BH portfolio. Furthermore, the correlation coefficients between six portfolios and value factor HML are relatively low also except for the BH portfolio (0.4570).

Table 1.5 Descriptive statistic of Fama-French 25 Size-B/P portfolios (July 2004- May 2015)

This table displays the descriptive statistic of FF 25 SBP portfolios for the period of July 2004 to May 2015 (131 months, 11 years). Across the columns of each panel are the five size portfolios which from Small to Big, and across the rows are the five B/P portfolios which from Low to High. Panel A is the value-weighted average excess returns of FF 25 Size-B/P portfolios, Panel B, C, and D are the annual average size, B/P ratio and firm numbers. The unit of size is 100 million 'yuan'.

	Book-to-price (B/P) ratio				
	Low	2	3	4	High
Panel A: Average excess returns					
Small	0.0123	0.0185	0.0173	0.0175	0.0172
2	0.0091	0.0128	0.0109	0.0111	0.0106
3	0.0055	0.0077	0.0090	0.0091	0.0089
4	0.0072	0.0052	0.0071	0.0067	0.0036
Big	0.0048	0.0029	0.0017	0.0025	0.0006
Panel B: Annual average size					
Small	1100	1189	1187	1207	1204
2	1880	1879	1881	1880	1893
3	2810	2808	2781	2807	2788
4	4731	4693	4693	4580	4658
Big	18937	22764	25721	25807	28974
Panel C: Annual average B/P ratio					
Small	-0.0066	0.2935	0.3881	0.5018	0.7094
2	0.0895	0.2937	0.3859	0.5020	0.7540
3	0.1474	0.2916	0.3879	0.5018	0.7385
4	0.1704	0.2866	0.3869	0.4992	0.7714
Big	0.1653	0.2874	0.3862	0.4995	0.7869
Panel D: Average number of firms					
Small	67	51	62	69	45
2	44	59	64	62	63
3	48	61	60	62	67
4	60	65	61	56	61
Big	78	63	52	49	62

Similar as Table 1.3, Table 1.5 represents the descriptive statistics of FF 25 Size-B/P portfolios on CNAS market for the period July 2004 to May 2015. Panel A shows the average excess returns of 25 portfolios, annual average size, B/P ratio and firm numbers of the 25 portfolios are shown in Panel B, C, and D respectively.

Evidence from Panel A is consistent with both FF findings and Table 1.3, across each B/P quintile, the average excess returns decrease with the size of portfolio increases. Still, there seems no regular variation across each size quintile. However, it is not so clear as six Size-B/P portfolios that higher B/ P ratio portfolios have relatively bigger size, and big size portfolios have relatively higher B/P ratio than small size portfolios. In Panel B, we cannot tell the difference except the biggest size quintile, in which the size of portfolios increases with B/P ratio. There is no obvious size difference across the B/P quintiles as showed in Panel C. Firm number of portfolios are relatively even, the portfolio of the biggest size and lowest B/P ratio has the most number of firms (78).

1.4.2.2 Time-series regressions

Table 1.6 shows the regression results obtained from the TSR of excess returns of six value-weighted Size-B/P portfolios on FF three factors, excess market returns, SMB and HML using a firm's tradable market value as a portfolio weight in computation of value-weighted returns and using all the market value to determine the breakpoints of size and B/P ratio groups. In Table 1.6, The left part of the table is the coefficients obtained from the regressions, a is the intercept, b , s and h are the regression coefficients s of FF three factors separately, and adjusted R-square. Correspondingly, the right part of the table is t-statistics and the standard error of estimation. Numbers in bold are the t-statistics which are significant at 5% confidence level. Coefficients of the market factor and SMB are all significant at the 5% confidential level, both are highly and positively related to stock returns, and three out of six coefficients are significant at the 5% level for HML factor. The adjusted R-squares are around 0.9 with averaged value 0.9081. The standard errors of estimation are relatively low and close to zero, which also means the satisfactory results. Overall, the regression results demonstrate that the FF3F explains most time-series variations of average excess stock returns on CNAS stock market during the research period.

According to the regression results, no one can ignore the significant role of the market factor in explaining Chinese stock returns. FF find that size and B/M equity are related to average expected portfolio returns (size is negatively related to averages expected returns and B/M ratio is positively related to expected returns), similarly on CNAS stock market

(Table 1.6), small firms have persistently higher returns (with regression coefficients of 1.2461, 1.1939 and 1.2133 for three small size portfolios) than big size firms (with regression coefficients 0.1669, 0.2867 and 0.1997). And across the size groups, firms with higher B/P ratio have higher returns and lower B/P ratio firms have relatively poor even negative returns. Besides, all the intercepts of six portfolios are not indistinguishable from zero, that is to say, FF three factors cannot completely capture the variation of excess returns.

Table 1.6 Time-series regression of six value-weighted Size-B/P portfolios on Chinese A-share stock market (July 2004- May 2015, 131 months)

The time-series regression results of six value-weighted Size-B/P portfolios on FF3F Model are displayed in this table. Across the columns are the two size groups (Small and Big) and across the rows are the three B/P ratio groups (Low, Medium and High). The left part of the table reports the coefficients obtained from the time-series regressions and adjusted R-square. Correspondingly, the right part of the table is t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator, and the standard error of the estimation. Numbers in bold are the t-statistics which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

	Book-to-Price (B/P) ratio					
	L	M	H	L	M	H
		a			$t(a)$	
S	0.0113	0.0135	0.0132	**4.8608**	**5.5340**	**5.1820**
B	0.0140	0.0118	0.0122	**5.6672**	**4.0914**	**4.9767**
		b			$t(b)$	
S	0.8766	0.8961	0.8767	**33.6953**	**33.6442**	**25.7726**
B	0.8469	0.9556	0.8468	**29.8677**	**22.6775**	**37.0579**
		s			$t(s)$	
S	1.2461	1.1939	1.2133	**16.8556**	**14.1879**	**13.7004**
B	0.1669	0.2867	0.1997	**2.1578**	**2.5084**	**2.8689**
		h			$t(h)$	
S	-0.0818	0.0187	0.3888	-0.8383	0.1912	**3.2870**
B	-0.6096	0.0157	0.9197	**-6.1817**	0.1125	**10.7208**
		Adj. R-square			Residual standard error	
S	0.9290	0.9239	0.9140	0.0256	0.0266	0.0283
B	0.8831	0.8818	0.9167	0.0271	0.0312	0.0254

Since the six portfolios can be criticized to have more bias and the results may have some coincidences. To be more convincing, and following what FF do in their paper of 1993, we construct 25 value-weighted Size-B/P portfolios on CNAS stock market using the same data sample. The TSR results of 25 Size-B/P portfolios are presented in Table 1.7.

Table 1.7 Time-series regressions of 25 value-weighted Size-B/P portfolios on FF3F Model, Chinese A-share stock market (July 2004 - May 2015; 131 months)

This table presents the time-series regressions results of 25 value-weighted Size-B/P portfolios on FF3F Model, Across the columns are five size groups and across the rows are five B/P groups. The left part of the table is the coefficients of the regressions and adjusted R-square. Correspondingly, the right part of the table is t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator, and the standard error of the residuals. Numbers in bold are the t-statistics which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

Size	B/P ratio									
	Low	2	3	4	High	Low	2	3	4	High
			a					$t(a)$		
Small	-0.0044	0.0024	0.0019	0.0019	0.0026	-1.5841	0.8853	0.8117	0.7198	0.9889
2	-0.0047	-0.0005	-0.0034	-0.0020	-0.0025	-1.5021	-0.1645	-1.3339	-0.7461	-0.9120
3	-0.0078	-0.0044	-0.0024	-0.0023	-0.0019	**-2.5702**	-1.6193	-0.9183	-0.8930	-0.7440
4	-0.0022	-0.0044	-0.0019	-0.0022	-0.0048	-0.7150	-1.5121	-0.7033	-0.7121	-1.7385
Big	0.0010	-0.0004	-0.0008	-0.0001	-0.0008	0.3856	-0.1371	-0.2218	-0.0480	-0.2678
			b					$t(b)$		
Small	0.9980	0.9790	0.9632	0.9921	1.0223	**20.9502**	**24.2296**	**30.0813**	**21.0168**	**25.6580**
2	1.0173	1.0115	1.0145	1.0217	0.9786	**23.1302**	**23.3347**	**24.8023**	**19.5580**	**19.5363**
3	1.0474	1.0065	1.0226	1.0397	1.0199	**14.2400**	**16.9243**	**25.6594**	**23.3416**	**21.1499**
4	0.9839	1.0161	1.0410	1.0642	1.0315	**19.2615**	**23.6557**	**20.3761**	**21.3104**	**19.0558**
Big	0.9902	1.0848	1.1129	1.0892	1.0192	**19.0456**	**21.8792**	**17.4111**	**24.0630**	**20.2916**
			s					$t(s)$		
Small	1.7215	1.6262	1.5829	1.6192	1.5391	**18.2026**	**17.7723**	**20.6765**	**15.6372**	**15.2212**
2	1.3944	1.3416	1.4422	1.3500	1.4211	**12.2720**	**15.2149**	**14.7213**	**11.7015**	**14.0101**
3	1.3131	1.2031	1.1731	1.2051	1.1870	**10.3210**	**10.2878**	**12.3951**	**12.7540**	**14.5117**
4	0.8990	0.9382	0.9173	0.9591	0.9775	**8.3352**	**8.5334**	**8.4023**	**9.5668**	**9.5371**
Big	0.2987	0.3186	0.3068	0.3811	0.3327	**2.7596**	**2.9922**	**2.1507**	**3.1433**	**2.8028**

Table 1.7 Continued

Size	B/P ratio									
	Low	2	3	4	High	Low	2	3	4	High
	h					$t(h)$				
Small	0.1368	-0.0191	0.1010	0.2561	0.3283	0.9822	-0.1547	1.0269	1.7704	**2.7737**
2	-0.1329	-0.0968	-0.0695	0.0646	0.5187	-0.8079	-0.6982	-0.6113	0.5000	**3.8859**
3	-0.3549	-0.2719	-0.0443	0.2148	0.4639	-1.8389	-1.7835	-0.3506	1.5733	**4.0028**
4	-0.5533	-0.4044	-0.1631	0.1485	0.5812	**-4.3698**	**-3.2740**	-1.2538	1.0347	**4.6418**
Big	-0.8710	-0.4303	-0.0341	0.3459	0.9049	**-6.1962**	**-2.8499**	-0.1969	**2.1630**	**6.6817**
	Adj. R-square					Residual standard error				
Small	0.8922	0.9282	0.9333	0.9122	0.9172	0.0389	0.0302	0.0284	0.0339	0.0330
2	0.9039	0.9100	0.9288	0.9065	0.9093	0.0346	0.0329	0.0296	0.0338	0.0330
3	0.8759	0.8924	0.8984	0.9063	0.9169	0.0403	0.0353	0.0343	0.0335	0.0311
4	0.8633	0.8907	0.8843	0.8859	0.9044	0.0378	0.0342	0.0358	0.0366	0.0331
Big	0.8670	0.8880	0.8747	0.8957	0.8949	0.0347	0.0340	0.0374	0.0339	0.0339

Similar as the TSR on FF six Size-B/P portfolios, the market factor still plays an important role in explaining the portfolio excess returns, as shown in each portfolio, all the coefficients of the market factor are dramatically significant. Regarding the size factor SMB and value factor HML, in accordance with (Fama and French, 1993) findings, that the average excess returns decrease as the firm size increase, the t-statistics (t-stats hereafter) of regression coefficients for the size factor are all significant at 5% confidence level. The excess returns have a positive relationship with firms' B/P ratio, firms with higher B/P ratio tend to have higher excess returns. The top 20% B/P ratio group has the most numbers of significant coefficients with t-stats 2.7737, 3.8859, 4.0028, 4.6418 and 6.6817 respectively, while the medium 20% group has none of the coefficients significant; and the bigger size portfolios seem to have more significant regression coefficients on HML. The adjusted R-squares are around 0.9 with averaged value 0.8995, the intercepts are all indistinguishable from zero except the portfolio in the third size quintile and the lowest B/P quintile in this regression, which means FF3F model captures the time-series variations of excess returns well on CNAS stock market.

The size and value effects on CNAS stock market are clearly shown in Figure 1.5. Figure 1.5 reports the TSR loadings on FF three factors (*b, s, h*) of the 25 Size-B/P portfolios (loadings are also reported in Table 1.7), separately. On the x-axis are the 25 portfolios from S1H1

Figure 1.5 Loadings of 25 Size-B/P portfolios on FF3F

This figure represents the time-series regressions loadings on FF three factors of 25 value-weighted Size-B/P portfolios – *b*, *s*, *h*, separately. On the x-axis are the 25 portfolios from S1H1 (smallest size and lowest B/P ratio) to S5H5(biggest size and highest B/P ratio), noting that in the middle panel, five portfolios of the same B/P quintile are grouped together in the order of increasing size, whereas in other two panels, five portfolios of the same size quintile are grouped together in the order of increasing B/P ratio.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

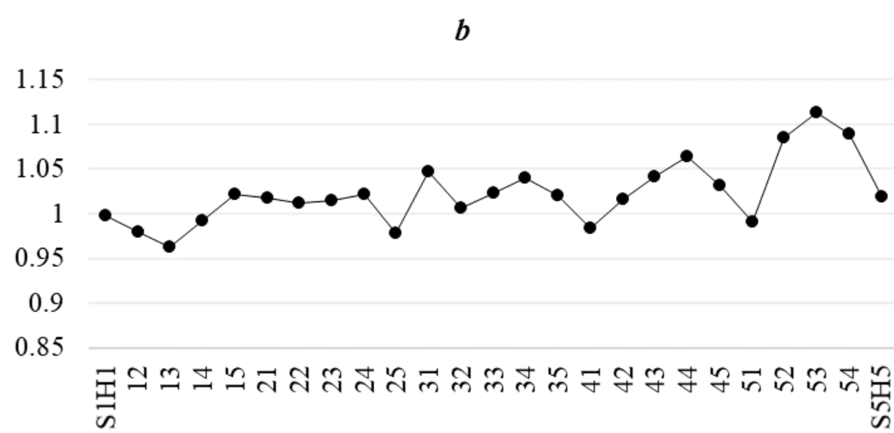
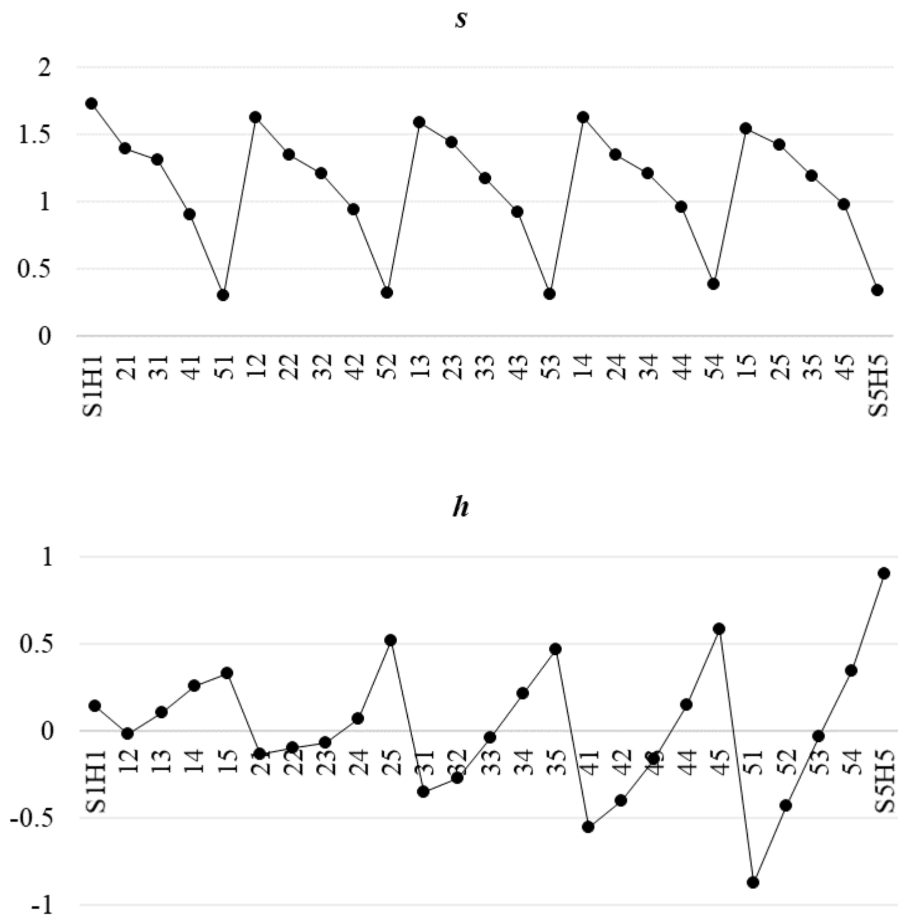


Figure 1.5 Continued



(smallest size and lowest B/P ratio) to S5H5(biggest size and highest B/P ratio), noting that in the middle panel, five portfolios of the same B/P quintile are grouped together in the order of increasing size, whereas in other two panels, five portfolios of the same size quintile are grouped together in the order of increasing B/P ratio. The three panels in Figure 1.5 are the loadings on excess market return (*b*), on SMB (*s*) and on HML (*h*). The loadings on SMB (s) show a clear monotonically decreasing relationship with size and the loadings on HML show a clear monotonically increasing relation with B/P ratio.

1.4.2.3 Cross-sectional results on Chinese stock market

The main contribution of FF3F Model is its success in explaining the cross-section stock returns in U.S market and many other stock markets in the world. We also examine whether FF3F Model can explain the cross-section variations of stock returns on CNAS stock market, both in the frame of 6 Size-B/P portfolios and 25 Size-B/P portfolios. FF apply (Fama and MacBeth, 1973) two-stage approach to perform the regressions, the first stage is the time-series which already demonstrated in previous research. The second stage is the cross-section regressions as shown in equation (1.16), where they use the estimated betas (in this research $\hat{b}$, $\hat{s}$ and $\hat{h}$) which are obtained from the first stage of TSR, as the independent variables in the CSRs. And regress the same portfolios' returns as in the first stage on these estimated betas for a fixed time period to determine the risk premium for each factor.

$$R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB} \hat{s}_i + \gamma_{HML} \hat{h}_i + \varepsilon_{i,t} \qquad (1.16)$$

Where:

$R_{i,t} - R_f$ is the excess returns of same portfolios as in the time-series (value-weighted FF six or 25 Size-B/P portfolios);

$\hat{b}_i$, $\hat{s}_i$ and $\hat{h}_i$ are the estimated coefficients from TSRs for the market factor, size factor SMB and value factor HML, separately;

γ_M , γ_{SMB} and γ_{HML} are the coefficients of CSRs.

Furthermore, it is important to recognize the classical Errors-in-variables (EIV) problem before we perform the CSRs, which occurs from the nature of Fama and MacBeth (1973) two-stage approach. When we applying standard OLS formulas to the second step of CSRs, the independent variables $\hat{\beta}$s are assumed to be given; however, $\hat{\beta}$s are estimated from the first step of TSRs, which are not fixed. Though Fama-Macbeth (FM) reduce the measurement error by running CSRs for portfolios instead of individual stocks, Shanken (1992) argues that the sampling errors for γs associated with the estimated betas still cannot be ignored. Shanken proposes that FM approach for computing standard errors keeps overstated the precision of the gamma estimates. Following Shanken (1992), we apply a correction procedure to solve the EIV problem. It assumes that the error terms from the TSRs are independently and identically distributed over time and independent of the factors. (Details of Shanken correction is presented in Appendix A)

According to our database, the cross-section regressions are performed at each month (131 months, from July 2004 to May 2015), for both FF six value-weighted Size-B/P portfolios and 25 value-weighted SBP portfolios, then the simple average of constants and coefficients, which are obtained from the 131 times CSRs on estimated betas (b, s and h) are calculated.

Table 1.8 shows the CSRs results on the estimated coefficients which obtained from the TSRs of FF 6 SBP value-weighted portfolios (Table 1.6) and 25 Size-B/P value-weighted portfolios (Table 1.7) separately. Panel A presents the CSR results of six value-weighted Size-B/P portfolios, and Panel B shows the CSR results of 25 value-weighted Size-B/P portfolios. γ_M , γ_{SMB} and γ_{HML} are the coefficients of the CSRs and their corresponding Fama-MacBeth (FM) and Shanken (SH) corrected t-stats are presented in the parentheses below the gammas.

The CSR results of FM show that neither of γ_M are significant at 5% confidence level (-0.0116 for the six portfolios with t-stats -0.6678, and -0.0251 for the 25 portfolios with t-stats -1.5912), which is consistent with most of researches on Chinese stock market that market beta is not able to explain the cross-sectional stock returns. Both γ_{SMB} of the two CSRs are

Table 1.8 Cross-sectional regressions of six value-weighted Size-B/P portfolios and 25 value-weighted Size-B/P portfolios, Chinese A-share stock market (July 2004- May 2015)

This table presents the results of cross-section regressions on FF3F Model of FF six value-weighted Size-B/P portfolios (Panel A) and 25 value-weighted Size-B/P portfolios (Panel B). In each panel, the first row is the cross-sectional regressions' coefficients (coef.); the second row is the corresponding Fama-MacBeth t-statistics (FM t-stats) at 5% confidence level and the third row is the Shanken corrected t-statistics (SH t-stats), which are in the parentheses. The numbers in bold are the t-stats which are significant at 5% level. The adjusted R-squares are percentage values.

Regression: $R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB} \hat{s}_i + \gamma_{HML} \hat{h}_i + \varepsilon_{i,t}$

	α	γ_M	γ_{SMB}	γ_{HML}	Adj. R^2 (%)
Panel A: Cross-sectional regressions of six Size-B/P portfolios					
gamma (coef.)	0.0224	-0.0116	0.0102	-0.0024	68.40
FM t-stats	(1.6619)	(-0.6678)	(**2.8861**)	(-0.8454)	
SH t-stats		(-1.4218)	(**2.8861**)	(-0.8404)	
Panel B: Cross-sectional regressions of 25 Size-B/P portfolios					
gamma (coef.)	0.0252	-0.0251	0.0085	-0.0004	49.01
FM t-stats	(1.7655)	(-1.5912)	(**2.2805**)	(-0.1200)	
SH t-stats		(**-3.0383**)	(**2.2882**)	(-0.1188)	

significant (0.0102 for the six portfolios with t-stat 2.8861 and 0.0085 for 25 portfolios with t-stats 2.2805), which proves the significant positive size premium of cross-sectional stock returns. After corrected by the Shanken correction, the SH t-stats is significant (-3.0383) for the market beta; while the important size premium is robust to the EIV adjustment. However, neither the FM or the SH t-stats indicate that there exists significant value premium. FF3F Model can explain more cross-sectional variation of six portfolios (with average adjusted R-squares 68.40%) than 25 portfolios (with average adjusted R-squares 49.01%) on Chinese stock market.

Consistent with most of previous studies, such as Wang and Xu (2004), Eun and Huang (2007), Wang and Iorio (2007) and Chen et al. (2015 working paper), the results of cross-section regressions in Table1.8 continue to prove that there is significant positive size premium across the stock returns on CNAS stock market during the periods July 2004 to May 2015. However, contrary to some researches, such as Wong et al. (2006), Eun and Huang (2007), Wang and Iorio (2007), Wu (2011) and Gan et al. (2013), we find the lack of value premium on CNAS stock market during our research period. Market beta is able to explain the cross-sectional variation in the average stock returns for the 25 value-weighted SBP portfolios with negative SH adjusted t-stats.

1.4.3 Comparing with U.S. market (FF3F Model)

Since the Chinese stock market has several special features that we take into account in our empirical research, it is important and interesting to compare the empirical results of Chinese stock market with those of U.S. market. We perform the same regressions with the same time interval from July 2004 to May 2015 using U.S. data. The FF three factors and the FF six (and 25) value-weighted Size-B/M portfolios are downloaded directly from the website of Kenneth R. French. All the empirical results of U.S. stock market are presented in Appendix B.

Table B.1 and Table B.2 reports the TSR results of FF3F Model on U.S. market during the period July 2004 to May 2015 (to be consistent with the time interval that we implement empirical analysis on Chinese stock market), respectively by regressing FF six value-weighted Size-B/M portfolios and 25 value-weighted Size-B/M portfolios on FF three factors, excess market return, SMB and HML.

We compare Table B.1 with Table 1.6, while Table B.2 with Table 1.7. It is observed that the time-series results on both countries are quite close. In Table B.1, all the loadings on market beta and five out of six loadings on SMB are statistically significant at 5% confidence level; while in Table B.2, still, all the loadings on market beta and 24 out of 25 loadings on SMB are significant. Take Table B.2 for example, more significant loadings (18 out of 25 on U.S. market, while 12 out of 25 on Chinese market) on HML of U.S. market indicates that the value factor has more explanatory power for the time-series variation of U.S. stocks than that of CNAS stocks.

There exist size and value effect on both CNAS stock market and U.S. stock market. Within each B/M group, the loading on SMB decreases as portfolio size increases, on U.S. market, there are even negative loadings of the portfolios that have big size; and within each size group, we find a positive relationship between the loading on HML and B/M ratio. Comparing the adjusted R-squares of Table B.2 and Table 1.7, which are higher on U.S. market (averaged adjusted R-squares is 0.9396) than on Chinese market (averaged adjusted R-squares is 0.8995). The results reveal that the time-series variation of stock returns captured by FF3F Model in U.S. is more than that captured by FF3F Model in China, that is to say, FF3F Model performs better on U.S. stock market than on CNAS stock market during the sample period.

We also perform the CSRs on FF3F Model using U.S. data, and the results are reported in Table B.3 (Appendix B). It is interesting that none of the regression coefficients on loadings of market beta, SMB and HML is significant; the results are robust to the EIV problem except the market beta for the six portfolios. For the 25 value-weighted Size-B/M portfolios, FF3F Model does not have any explanatory power of the cross-sectional variation of stock returns on U.S. market over the period July 2004 to May 2015. FF3F Model performs better in capturing cross-sectional variation of average excess stock returns on CNAS stock market (with averaged adjusted R-square 68.40% of the six portfolios and 49.01% of the 25 portfolios) than on U.S. stock market (with adjusted R-square 58.14% and 40.76% for the six and 25 Size-B/P portfolios separately) over the research period.

1.5 Construction of profitability and investment factors and empirical results of FF5F Model

1.5.1 Construction problems

Table 1.9 shows the annual available number of firms which have available OP and Inv data from 2004 to 2014. The number of firms that has available data of OP are always less available than that of Inv, and before 2009, there are few firms (less than 30) that have available OP.

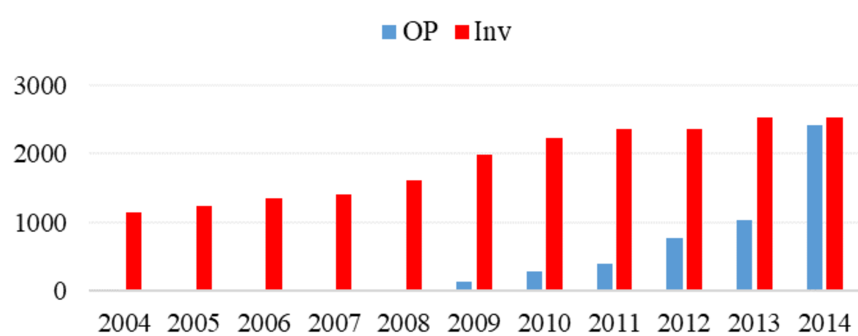
Table 1.9 Annual firm numbers that have available data of OP and Inv (2004-2014)

This table presents the annual number of firms that have available OP and Inv data from 2004 to 2014.

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
OP	12	17	24	26	27	131	294	392	777	1043	2417
Inv	1154	1237	1346	1402	1624	1981	2241	2355	2361	2525	2525

The annual available number of firms that has available OP and Inv are visually displayed in Figure 1.6, the blue bar is operation profitability and the red bar is investment opportunity, the x-axis indicates the year and the y-axis indicates the firm numbers. It is obvious that the number of firms that has OP are much less than that has Inv until the year 2014. And there are few available data of OP before 2010. To be more accurate and reduce the bias generated because of the very few firm numbers (when we sort firms into portfolios, there may be no firms in portfolios with firm numbers less than 30 in a year), we exclude the data before 2010.

Figure 1.6 Annual number of firms that has available data of OP and Inv



FF (2015a) perform the TSR using 25 Size-B/M Portfolios, 25 Size-OP portfolios and 25 Size-Inv portfolios. Following the same method, firstly we construct these portfolios on CNAS stock market. The construction of Size-OP portfolios and Size-Inv portfolios are similar as the method to construct 25 Size-B/P portfolios on Chinese stock market (refer to the section 1.2.1.1), just the B/P ratio is replaced by OP or Inv.

Table 1.10 shows the annual number of stocks in 25 Size-OP portfolios and 25 Size-Inv portfolios, in which, S indicates the size group, P is the profitability groups and I is the investment groups. For instance, S1P1 portfolio indicates the intersection of firms in the bottom 20% size quintile and firms in the bottom 20% OP quintile. It is obvious that there are more stocks of Size-Inv portfolios than that of Size-OP portfolios. Furthermore, there are no firms in several Size-OP portfolios (portfolio S1P2 of the year 2010, portfolio S2P5 of the year 2010 and 2012), and all the portfolios except one (portfolio S2P1 of the year 2011) of the year 2010 and 2011 have no more than 5 firms. In this case, we use the frame of six portfolios to test FF5F model on CNAS stock market instead of the 25 portfolios.

Table 1.10 Annual number of stocks in 25 Size-OP portfolios and 25 Size-Inv portfolios (2010-2014)

This table presents the annual firm numbers in each 25 Size-OP portfolios (left-hand part) and 25 Size-Inv portfolios (right-hand part) from 2010 to 2014, in which, S indicates the size group, P is the profitability groups and I is the Investment groups. For instance, S1P1 portfolio indicates the intersection of firms in the bottom 20% size quintile and firms in the bottom 20% OP quintile.

	Year										
	2010	2011	2012	2013	2014		2010	2011	2012	2013	2014
S1P1	1	5	27	38	167	S1I1	155	131	130	152	149
S1P2	0	4	20	39	131	S1I2	82	67	89	111	112
S1P3	1	1	7	15	86	S1I3	44	56	72	70	80
S1P4	1	1	2	6	44	S1I4	32	52	49	52	56
S1P5	3	1	2	4	21	S1I5	19	90	100	64	64
S2P1	5	8	25	41	129	S2I1	87	88	116	105	121
S2P2	2	2	17	34	113	S2I2	68	97	92	108	113
S2P3	1	2	16	23	104	S2I3	60	56	69	93	97
S2P4	2	2	3	6	73	S2I4	50	48	73	63	68
S2P5	0	4	0	5	28	S2I5	66	108	88	83	62
S3P1	5	5	30	42	88	S3I1	66	94	82	109	92
S3P2	3	8	31	42	107	S3I2	81	89	101	99	101
S3P3	3	2	7	27	104	S3I3	71	69	98	86	100
S3P4	0	0	2	5	101	S3I4	54	60	73	84	94
S3P5	1	3	3	5	45	S3I5	60	82	86	73	75
S4P1	21	25	33	45	54	S4I1	55	69	77	72	69
S4P2	18	21	37	46	83	S4I2	60	90	99	83	95
S4P3	9	17	31	44	110	S4I3	81	84	84	106	95
S4P4	9	12	9	27	126	S4I4	65	78	85	100	96
S4P5	2	4	5	10	69	S4I5	69	75	95	91	108
S5P1	27	35	40	41	42	S5I1	35	41	55	51	59
S5P2	34	43	48	45	49	S5I2	64	90	71	83	66
S5P3	42	53	75	78	72	S5I3	77	112	113	98	91
S5P4	39	62	72	78	109	S5I4	84	100	128	125	122
S5P5	31	53	46	61	166	S5I5	71	53	72	94	124

1.5.2 Empirical results of Fama-French Five-Factor Model on Chinese A-share stock market

1.5.2.1 Summary information of factors and portfolios

Then we sort portfolios into six value-weighted Size-OP portfolios and six value-weighted Size-Inv portfolios, the annual number of firms in the two sets of portfolios are displayed in Table 1.11. The small size groups of Size-OP portfolios relatively have fewer stocks than that of big size groups and the SR portfolio has no stocks in the year 2009 and only one stock in SN portfolio. Therefore, because of the lack of data on firm numbers of CNAS stock market, the interval of our research to processing FF5F model is from July 2010 to May 2015 (59 months).

Table 1.11 Annual number of stocks in six Size-OP portfolios and six Size-Inv portfolios

This table presents the annual firm numbers of six Size-OP portfolios (Panel A) and six Size-Inv portfolios (Panel B) from 2009 to 2014. In the first column of Panel A presents the six Size-OP portfolios (SW, SN, SR, BW, BN and BR), and in the first column of Panel B shows the six Size-Inv portfolios (SC, SN, SA, BC, BN and BA).

Year	2009	2010	2011	2012	2013	2014
Panel A Size-OP portfolios						
SW	5	11	22	92	154	488
SN	1	7	7	52	107	483
SR	0	5	9	7	13	146
BW	34	76	95	140	157	233
BN	51	104	147	210	255	468
BR	28	57	93	87	121	403
Panel B Size-Inv portfolios						
SC	328	374	392	404	457	465
SN	262	288	310	380	412	444
SA	105	167	289	314	258	244
BC	187	203	244	277	274	268
BN	301	373	468	492	496	479
BA	206	251	276	330	358	409

As shown in Table 1.12, Panel A is the summary statistics of FF five factors on Chinese stock market, the mean, standard deviation, standard error, sample variance and so on. Panel B is the correlation coefficients among the FF five factors, the profitability and investment factors are both positively related to market factor with low correlation coefficients (0.0418 and 0.1190) and negative related to size factor (-0.2227 and -0.2199).

RMW is negatively related to value factor HML (-0.0217), while CMA is positively and relative highly related to HML with correlation coefficients of 0.4621. And the correlation coefficients between RMW and CMA is -0.3121.

Table 1.12 Summary statistics of Fama-French five factors (July 2010-May 2015)

Panel A report the summary statistics of FF five factors, it summarizes the mean, standard error (Sd error), standard deviation (S.D), variance, kurtosis and skewness. Panel B reports the correlation coefficients among the five factors.

Panel A: Summary statistics of FF five Factors					
	$R_{M,t} - R_f$	SMB	HML	RMW	CMA
Mean	-0.0014	0.0106	-0.0059	-0.0061	0.0008
Sd error	0.0084	0.0038	0.0046	0.0036	0.0025
Median	-0.0024	0.0117	-0.0075	-0.0128	0.0001
S.D	0.0646	0.0294	0.0355	0.0273	0.0196
Variance	0.0042	0.0009	0.0013	0.0007	0.0004
Kurtosis	0.2068	6.4386	5.9071	-0.4204	-0.2635
Skewness	0.1439	-1.2015	0.5658	0.3288	0.2217
Panel B: Correlation coefficients among FF five factors					
RM-RF	1				
SMB	0.1165	1			
HML	-0.0013	-0.6970	1		
RMW	0.0418	-0.2227	-0.0217	1	
CMA	0.1190	-0.2199	0.4621	-0.3121	1

Table 1.13 presents the average excess return of six Size-B/P portfolios (Panel A), Size-OP portfolios (Panel B) and Size-Inv portfolios (Panel C). Across the columns are the two size groups and across the rows are the three B/M groups, three OP groups, and three Inv groups, respectively. It is apparent that there is the size effect, the big size portfolios always have the lower returns than the small size portfolios in each panel. Across the OP groups in Panel B, it is strange that the robust portfolios have lower returns than weak portfolios, perhaps the lack of data for OP causes the bias. Across the Inv groups in Panel C, it seems the neutral investment portfolios have the highest excess returns (0.0158 for small size and neutral investment portfolio, 0.0050 for big size and neutral investment portfolio) than the conservative and aggressive investment portfolios.

Table 1.13 Average monthly excess returns for portfolios formed on Size-B/M, Size-OP and Size-Inv (July 2010-May 2015, 59 months)

The average excess returns of six Size-B/M portfolios, Size-OP portfolios, and Size-Inv portfolios are presented in panel A, B and C respectively. Across the columns are the two size groups (Small and Big) and across the rows are the three B/M groups (Low, Medium and High), three OP groups (Weak, Neutral and Robust) and three Inv groups (Conservative, Neutral and Aggressive), respectively.

Panel A: Excess returns of size-B/M portfolios			
	L	M	H
S	0.0236	0.0231	0.0207
B	0.0151	0.0092	0.0061
Panel B: Excess returns of Size-OP portfolios			
	W	N	R
S	0.0172	0.0170	0.0081
B	0.0046	0.0082	0.0016
Panel C: Excess returns of Size-Inv portfolios			
	C	N	A
S	0.0136	0.0158	0.0121
B	0.0033	0.0050	0.0031

1.5.2.2 Time-series regressions of FF5F model on Chinese A-share stock market

To understand how FF five factors explain the excess return of these portfolios, the TSRs are performed on six Size-B/P portfolios, Size-OP portfolios and Size-Inv portfolios on FF five factors for the period of July 2010 to May 2015 (59 months). The results are demonstrated in Table 1.14, Panel A, Panel B and Panel C are the TSRs results for the value-weighted six Size-B/P portfolios, six Size-OP portfolios and six Size-Inv portfolios, separately. The loadings on market beta (*b*) are similar for the three sets of portfolios, they are all highly significant at 5% confident level.

We next look at each panel, in Panel A, five out of six (except the portfolio of big size and high B/P ratio) loadings on size factor SMB are significant at 5% confidence level, and the signs of slopes indicate that portfolios of small size have returns that are positively related to SMB, while returns of big size portfolios are negatively related to SMB. All the loadings on HML are highly significant, there exists consistently size and value effect in the regressions of six value-weighted Size-B/P portfolios on FF5F Model. However, none of the loadings on

Table 1.14 Time-series regressions of six value-weighted Size-B/P portfolios, Size-OP portfolios and Size-Inv portfolios on FF5F Model, Chinese A-share stock market (July 2010 to May 2015, 59 months)

This table presents the time-series regressions results of FF5F model. In each panel, the regression intercept a, the regression coefficients b, s, h, r and c of market factor, size factor, value factor, profitability factor and investment factor, adjusted R square are respectively presented in the left part of the table, the corresponding t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator and residual standard error are presented in the right part. Panel A is the regressions on six Size-B/P portfolios, across the columns are the two size groups (Small and Big) and across the rows are the three B/P groups (Low, Medium and High). Panel B is the regression results of six Size-OP portfolios, same as Panel A, across the columns are the two size groups and across the rows are the three OP groups (Weak, Neutral and Robust). Panel C is the regression results of six Size-Inv portfolios, across the columns are the two size groups and across the rows are the three Investment groups (Conservative, Neutral and Aggressive). Numbers in bold are the t-stats which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{i,t}$

Panel A Time-series regressions of six Size-B/P portfolios						
	Book-to-Price (B/P) ratio					
	L	M	H	L	M	H
		a			$t(a)$	
S	0.0102	0.0105	0.0108	**7.4308**	**4.4938**	**5.6696**
B	0.0124	0.0091	0.0118	**6.8522**	**3.8634**	**6.4458**
		b			$t(b)$	
S	0.9637	0.9964	0.9703	**41.1513**	**36.2183**	**35.8284**
B	0.8361	1.0214	0.8295	**27.6969**	**28.5669**	**20.8687**
		s			$t(s)$	
S	1.0039	0.9383	0.8557	**15.9153**	**16.3385**	**11.3131**
B	-0.1946	-0.2434	-0.0465	**-2.8370**	**-2.4971**	-0.5165
		h			$t(h)$	
S	-0.5849	-0.5197	-0.2689	**-6.2171**	**-6.9004**	**-3.9751**
B	-0.9928	-0.6007	0.6912	**-12.4860**	**-7.2244**	**5.1532**
		r			$t(r)$	
S	-0.0695	-0.1448	-0.0617	-1.1264	-1.9122	-0.7331
B	0.0188	-0.0456	0.0110	0.2597	-0.6538	0.1965
		c			$t(c)$	
S	0.2515	0.1051	0.3064	**2.6156**	1.0264	**2.3582**
B	0.1114	0.2802	0.0565	1.2338	**3.4851**	0.5584
		Adj. R-square			Residual standard error	
S	0.9782	0.9714	0.9606	0.0120	0.0137	0.0148
B	0.9625	0.9609	0.9513	0.0122	0.0136	0.0134

Table1.14 Continued

Panel B: Time-series regressions of six Size-OP portfolios						
	Operating Profitability					
	W	N	R	W	N	R
		a			*t* (*a*)	
S	0.0012	0.0020	-0.0018	0.5498	0.4592	-1.0778
B	-0.0009	0.0028	0.0021	-0.5008	1.4503	0.6190
		b			*t* (*b*)	
S	1.0075	1.0408	1.0492	**35.8879**	**20.1490**	**31.7018**
B	1.1300	1.0253	1.0883	**26.7879**	**34.3991**	**25.3012**
		s			*t* (*s*)	
S	1.1712	0.9800	1.5637	**13.2828**	**5.5382**	**18.1679**
B	0.2480	0.2628	-0.1445	**2.3517**	**3.3480**	-1.1030
		h			*t* (*h*)	
S	-0.4482	-0.7244	-0.2020	**-4.5108**	**-3.9157**	-1.9726
B	-0.4560	-0.5496	-0.7022	**-4.4978**	**-5.9760**	**-6.6825**
		r			*t* (*r*)	
S	-0.3429	-0.2601	1.1319	**-4.6763**	**-2.5519**	**15.7233**
B	-0.2265	-0.1198	0.2987	**-3.5011**	-1.3591	**3.4009**
		c			*t* (*c*)	
S	0.2644	0.1610	0.5398	**2.4244**	0.7310	**4.2483**
B	0.4613	0.0414	0.1860	**5.8956**	0.3561	1.3955
		Adj. R-square			Residual standard error	
S	0.9720	0.9301	0.9653	0.0143	0.0238	0.0172
B	0.9643	0.9640	0.9486	0.0150	0.0139	0.0172
Panel C: Time-series regressions of six Size-Inv portfolios						
	Investment					
	C	N	A	C	N	A
		a			*t* (*a*)	
S	-0.0016	0.0018	-0.0017	-0.9026	0.8186	-1.0068
B	-0.0030	0.0003	-0.0029	-1.5819	0.1566	-1.5573
		b			*t* (*b*)	
S	1.0708	1.0548	1.0274	**31.3516**	**33.9728**	**35.4151**
B	1.0683	1.0704	1.1116	**27.9726**	**32.5243**	**27.7982**
		s			*t* (*s*)	
S	1.2837	1.1137	1.1998	**18.0777**	**14.7519**	**14.5888**
B	0.4139	0.3165	0.4978	**4.0713**	**4.7070**	**5.5174**

Table1.14 Continued

Panel C: Time-series regressions of six Size-Inv portfolios						
	Investment					
	C	N	A	C	N	A
		h			*t* (*h*)	
S	-0.2393	-0.5369	-0.5135	**-2.2282**	**-6.2005**	**-4.8437**
B	-0.6269	-0.4482	-0.3527	**-5.9485**	**-5.6888**	**-3.2055**
		r			*t* (*r*)	
S	-0.1329	-0.0789	-0.0871	-1.3784	-0.8737	-0.9804
B	0.0481	-0.0330	0.0023	0.5404	-0.5768	0.0249
		c			*t* (*c*)	
S	-0.7507	-0.0210	0.5330	**-4.8137**	-0.2007	**3.2129**
B	-0.2540	0.0445	0.4623	-1.9740	0.4260	**3.7475**
		Adj. R-square			Residual standard error	
S	0.9722	0.9713	0.9739	0.0148	0.0149	0.0141
B	0.9607	0.9680	0.9595	0.0157	0.0135	0.0160

the profitability factor RMW is significant, while three out of six loadings on the investment factor CMA are significant at 5% confidence level.

Comparing the TSRs in Panel A with those (Appendix C, Panel A of Table C.1) of the six value-weighted SBP portfolios on FF3F model over the same time interval (July 2010 to May 2015), the results are quite similar for FF three factor (market beta, SMB, and HML). The adjusted R-squares are much close between both regressions on FF3F Model and FF5F Model, it is suggested that FF profitability and investment factors seem not add explanatory power in capturing time-series variation of excess stock returns on CNAS stock market during the sample period.

In Panel B, the regression results for market beta, SMB, and HML are fairly close to those of Panel A, the big difference is in profitability factor RMW, all loadings on RMW except the portfolio BN are significant; and in each size group, portfolios with robust profitability tend to have higher excess returns than portfolios with weak profitability. Three out of six coefficients of investment factor CMA are significant, two are the portfolios with weak profitability (0.2644 for portfolio SW with t-stats 2.4244 and 0.4613 for portfolio BW with t-stats 5.8956) and one is the portfolio SR (coefficients 0.5398 with t-stats 4.2483).

Comparing to the regressions of the same six value-weighted Size-OP portfolios on the original FF3F Model on Chinese stock market (Appendix C, Panel B of Table C.1), in the presence of RMW and CMA, FF original three factors do not lose their explanatory power.

Comparing the adjusted R-square of both regressions, FF5F Model explains slightly more variations of time-series average returns (with averaged adjusted R-square 0.9574) than FF3F Model (with averaged adjusted R-square 0.9256) of the six value-weighted Size-OP portfolios.

In Panel C, the regression results of the market factor, SMB, and HML are all satisfactory significant. The loadings on RMW are similar to Panel A, none of which is significant at 5% confidence level. As for the CMA factor, three out of six loadings are significant, furthermore, the three significant loadings are of the portfolios with conservative and aggressive investment. And the investment effect is close to the results of 25 Size-Inv portfolios of Fama and French (2015a), the aggressive investment portfolios tend to have smaller even negative regression loadings, while the conservative investment portfolios have relatively bigger regression loadings. In other words, there exist investment effect and the firm's investment is negatively related to average excess stock returns. Comparing to the regression results of the same portfolios but on FF3F Model (Appendix C, Panel C of Table C.1), it is suggested that RMW and CMA factors seem not add explanatory power in capturing time-series variation of the six value-weighted Size-Inv portfolios' returns (the averaged adjusted R-square are 0.9658 for FF3F Model and 0.9676 for FF5F Model), neither.

To summarize, market beta always plays an important role in explaining time-series variation of excess portfolio returns. For all the three sets of portfolios, there exists size effect that the excess returns are negatively related to firm size. While there exists value effect in SBP portfolios, profitability effect in Size-OP portfolios and investment effect in Size-Inv portfolios. The loadings on RMW are only significant in the set of portfolios sorted by size and OP, but not in two other sets of portfolios. As to the CMA factor, the significant loadings are concentrated in the extreme OP or Inv groups (such as the weak OP group, robust OP group, the aggressive and conservative Inv groups). However, for the Size-B/P portfolios, the CMA significant coefficients are relatively dispersive. In short, whether FF5F Model performs better than FF3F Model on CNAS stock market over the sample period is not quite clear. The explanatory power of FF5F Model seems differs among different sets of portfolios. In comparison with FF3F Model, the presence of profitability and investment factors seem not capture more variations of expected stock returns than the three-factor model except for the six value-weighted portfolios formed on size and OP, though the improvement is limited.

1.5.3 Comparing with U.S. stock market (FF5F Model)

Similarly, we compare the performance of FF5F Model on both CNAS stock market and on U.S. stock market. We implement the same regressions in the previous section as reported in Table 1.14 but using data of U.S. market. The six value-weighted Size-B/M portfolios, six Size-OP portfolios, and six Size-Inv portfolios are downloaded directly from Kenneth R. French's website, the TSR results of the three sets of portfolios are presented in Appendix B (Table B.4). The loadings on the excess market return are always strongly positive for all three sets of portfolios of both countries. The loadings on SMB are strongly positive for small stocks and slightly positive or negative for big stocks, there exists size effect on both stock markets.

We next compare between each panel of Table 1.14 (Chinese market) and Table B.4 (U.S. market). Comparing 'Panel A' of both tables, there exists value effect on both stock markets. As to the profitability factor RMW, four out of six loadings on RMW are statistically significant and especially all three loadings on small portfolios are negative significant in U.S.; while none of the loadings on RMW is significant at 5% confidence level in China.

Comparing Panel B of both tables, the regression results of six Size-OP portfolios are approximately close. All the loadings on profitability factor RMW are strongly significant, among which the loadings are strongly negative for the weak OP portfolios (low profitability) and strongly positive for the robust OP portfolios (high profitability) on U.S. stock market; while five out of six loadings on RMW are significant on CNAS stock market with the same pattern as U.S. market. It is noticed that the loadings on CMA factor are significant only for the three big size portfolios in U.S. We find no apparent value effect when regressing the six Size-OP portfolios on FF5F Model on both stock markets.

The regression results for the six Size-Inv portfolios are quite different comparing Panel C of both markets. First, most loadings on HML lose their significance (only one out of six is significant) in U.S.; while all the portfolios have strong negative exposure to HML on Chinese stock market but no value effect. Then the small size portfolios always have significant exposure to RMW in U.S.; while none of the loadings on RMW is significant on CNAS stock market for the Size-Inv portfolios. Last, CMA factor seems explains more time-series variation of excess stock returns in U.S. than in China, since all the loadings on CMA are significant while only four out of six loadings are significant on Chinese stock market. The slopes of conservative (low investment) portfolios are positive and the slopes of aggressive (high investment) portfolios are negative on both markets, which is consistent with FF's expected pattern.

Furthermore, the adjusted R-squares of six Size-OP portfolios (with averaged adjusted R-squares 0.9545 on Chinese market, and 0.9861 on U.S. market) and six Size-Inv portfolios (with averaged adjusted R-squares 0.9676 on Chinese market, and 0.9855 on U.S. market) are slightly bigger in U.S than that in China, which indicates that FF5F Model explains the two sets of portfolios slightly better on U.S. stock market than on CNAS stock market. In addition, the profitability factor and investment factor are able to capture partially time-series variation of all three sets of portfolios' returns on U.S. stock market, while on Chinese stock market, the profitability factor seems to be an explanatory factor only for the six value-weighted Size-OP portfolios.

1.6 Conclusions

Fama and French draw a conclusion that risk (market beta) was not able to identify all the stock return variations during 1963-1990 on US stock market, two other factors, size and book-to-market equity, combined to capture the cross-sectional variation in average stock returns unite with market β. To investigate whether size and value factors also explain excess returns on Chinese stock market, this chapter first performs the empirical tests of FF3F Model on CNAS stock market.

As the results shown in the empirical tests on CNAS stock market (July 2004-May 2015), FF3F model can explain a majority of time-series variation of the stock returns, when using tradable market value to weight the portfolios, total market capitalization to decide the size breakpoint and book-to-price ratio instead of B/M equity ratio. We conduct the CSRs and the results are consistent with most of the previous studies on Chinese stock market, there exists positive size premium across the stock returns on CNAS stock market, however, we find no value premium during the periods July 2004 to May 2015. While after adjusted by Shanken correction, the market beta is also a determinant factor in explaining the cross-sectional excess stock returns (25 value-weighted Size-B/P portfolios).

Despite the quite significant results of regressions on CNAS stock market, FF three factors (size factor and book-to-market equity combined with the market factor) still cannot explain all the variation of stock returns.

According to Fama and French, firm size and B/M equity ratio are related to the systematic pattern of profitability and growth. They are potentially major sources of risk in return. These two mentioned variables were known in most studies as two specific market indicators that raise questions about the model. These findings diminished the credence of this model, and a new wave was formed in the development field of financial theories with the aim of explaining the causes of these special consequences.

Based on the valuation theory and recent empirical findings on the strong profitability and investment effects in asset returns, FF (2015a) propose a five-factor model contains the market factor and factors related to size, book-to-market equity ratio, profitability and investment. We apply FF5F Model on CNAS stock market during the period July 2010 to May 2015 and construct three sets of portfolios similarly as FF, six value-weighted Size-B/P portfolios, six value-weighted Size-OP portfolios and six value-weighted Size-Inv portfolios. For all the three sets of portfolios, market factor, size factor and value factor have strong explanatory power for the expected excess returns in the presence of profitability and investment factors. There always exists size effect that the excess returns are negatively related to firm size, while there exists value effect in Size-B/P portfolios, profitability effect in Size-OP portfolios and investment effect in Size-Inv portfolios. The CMA factor do have explanatory power for certain portfolios in all three sets of portfolios. However, the RMW factor only has explanatory power in six Size-OP portfolios.

In comparison with FF3F Model, profitability and Investment factors seem not having much additional explanatory power except for the six value-weighted portfolios formed on size and OP. The explanatory power of FF5F Model seems differs among different sets of portfolios comparing with the original three-factor model on CNAS stock market during the research period July 2010 to May 2015. Since the research period is relatively short in this study, we suggest to apply the examination with a longer time interval for the FF5F Model on Chinese stock market in the future.

We also implement the regressions that performed on CNAS stock market over the same period using U.S. data. The empirical results reveal that both FF3F Model and FF5F Model explain slightly better time-series variation of average excess stock returns on U.S. stock market than on CNAS stock market. As for the two additional factors, profitability factor and investment factor are able to capture partially time-series variation of all three sets of portfolios' returns on U.S. stock market, while on Chinese stock market, the profitability factor seems to be an explanatory factor only for the six Size-OP portfolios. Surprisingly, we find that FF3F Model do not have cross-sectional explanatory power on U.S stock market from July 2004 to May 2015.

Write between Chapter 1 and Chapter 2

Empirical research into the CAPM first documented that market risk was a factor that did not perform well in explaining cross-sectional stock returns, then documented that other factors - size factor SMB and value factor HML - did perform well in explaining stock returns. Researchers had already observed that small stocks earned higher returns than large stocks, and high book-to-market stocks earned higher returns than low book-to-market stocks. Fama and French (1993) constructed factors on the basis of this observation, and propose the FF3F Model. They demonstrated that the size and value factors did, indeed, perform quite well in explaining cross-sectional stock returns. It is no exaggeration to say that since the publication by Fama and French (1993), the FF3F Model has been accepted as the most widely used expected returns model amongst researchers, and has become the cornerstone of factor studies.

However, as is well-known that FF factors are based on purely empirical work, and there is no clear theoretical foundation to identify the risk factors, which makes it one of the most controversial asset pricing model. The huge success of FF3F Model lead to the question that whether there is a body of theory to support the use of the particular factors that Fama and French have identified. For next two decades a substantial body of literature devoted to theoretical explanations for the explanatory power of SMB and HML.

There is debate amongst researchers who have attempted to explain why it is the two FF factors explain stock returns and what risks are reflected in the size and book-to-market factors. One dominant theoretical explanation is based upon the asset pricing theory already established well before the empirical papers by FF – the Intertemporal CAPM (ICAPM) of Merton (1973).

In the one-period CAPM, investors do not need to consider what happens outside of their investment horizon. This is the basis for the intertemporal term in the model. While the ICAPM assumes that investors trade continuously and maximize their expected utility of lifetime consumption; investors care about what happens after the initial investment ends, so will care about risks associated with future developments in the economy. So assets will be priced, in a multi-factor model, according to investor expectations about future states of the economy. For instance, investors might be concerned about future investment opportunities. Over longer time periods, investment opportunities might shift as expectations of risk change, resulting in situations in which investors may wish to hedge. In other words, investors will seek to hedge against not only shocks to wealth as in the traditional CAPM, but also against shocks to future investment opportunities.

The main difference between ICAPM and traditional CAPM is the additional state variables such as economic variables that acknowledge the fact that investors hedge against changes in the future investment opportunity set. The ICAMP is a linear factor model with wealth and state variables that forecast changes in the distribution of future returns or income.

Our empirical results of chapter 1 demonstrate the applicability of FF3F Model on CNAS stock market during July 2004 to May 2015; specifically, the size factor SMB explains the cross-sectional variation of average excess stock returns well during the sample period. Such results give rise to the questions: what are the economic explanation of FF factors on Chinese stock market? Could they be explained in the context of ICAPM which has been proved to be so by such as Petkova (2006) in the U.S stock market?

In order to answer the questions, we implement in the following chapter the theoretical explanation based on time-varying investment opportunities in the frame of ICAPM using data of CNAS stock market. Following Campbell (1996) who suggest using innovations in state variables to forecast the changes in the future investment opportunity set, instead of using the state variables directly for the empirical implementation of the ICAPM, we consider the innovations of state variables that capture uncertainty about future investment opportunities in our research; and examine whether FF factors proxy for innovations of selected state variables on CNAS stock market.

2 Fama-French Factors and Innovations in State Variables on Chinese A-Share Stock Market

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This chapter examines whether the innovations of the four predictive variables (aggregate dividend yield, one-month T-bill rate, term spread and default spread) are able capturing excess stock returns in both time-series and cross-section, further whether Fama-French factors SMB and HML proxy for the innovations of selected state variables that describe future investment opportunities on Chinese A-share stock market. To derive the innovation terms, we apply the vector autoregressive (VAR) method. Following, Fama-MacBeth two-stage approach method is implemented to perform the regressions for five models, and Shanken correction is also performed to adjust for the Errors-in-Variables problem in the cross-sectional regressions. Then the comparisons are made among the five models.

2.1 Economic explanation of Fama-French factors in the context of ICAPM

FF3F Model has achieved huge empirical success since it came up, which makes it a popular as well as one of the most controversial asset pricing models. However, these factors are based on purely empirical considerations, lack theoretical underpinnings, and are built in a rather arbitrary manner. In particular, their economic links to systematic risk are not clear. Therefore, the impressive performance of FF3F Model has aroused numerous researches that trying to providing a clear economic interpretation of the factors HML and SMB.

Some researchers attribute the success of FF factors to the survivor bias (Kothari et al., 1995b), and data snooping (MacKinlay, 1995b). Lakonishok et al. (1994b) argue that the B/M effect reflect investors' incorrect inference of firms' past earnings growth, suggesting that investors undervalue firms with poor past performances while they overvalue firms that have performed well in the past. Daniel and Titman (1997), however, suggest that it is the characteristics of stocks rather than the covariance structure of returns that appear to explain the cross-sectional variation in stock returns. While more researchers focus on the alternative factors (such as macroeconomic variables) that are able to capture the variation of equity returns in addition to the market return and have economic significance[19].

The underlying economic links of FF factors are rather controversial, among plenty competing explanations for the success of FF3F Model, following Petkova (2006), in this chapter we focus on the one based on time-varying investment opportunities which is in the context of Merton (1973a)'s Intertemporal Capital Asset Pricing Model (ICAPM hereafter).

2.1.1 ICAPM framework

Intertemporal Capital Asset Pricing Model (ICAMP) is put forward by Merton (1973a), which as an improvement or extension of CAMP of Sharpe (1964) and Lintner (1965). It is well documented in the literature that the CAPM is a static model which assumes betas remain constant over time and that the return on the value-weighted portfolio of all stocks is a proxy for the return on aggregate wealth. However, the single-period nature of CAPM has been criticized, since most investors do not participate in financial markets for one year,

[19] For example, Jagannathan and Wang (1996) include a labor income growth factor which performs well in explaining the cross-section of average returns, Li, Vassalou, and Xing (2006) introduce Sector Investment Growth Rates, Liew and Vassalou (2000) document that the size and B/M factors predict future economic growth in some countries, Vassalou (2003) find that much of information contained in the size and B/M factors is related to future GDP growth.

but instead for multiple years. Over longer time periods, investment opportunities might shift as expectations of risk change, resulting in situations in which investors may wish to hedge. For example, an increase in expected future returns will have a positive effect on current consumption through decreased savings, in addition, an increase in the expected volatility of returns will have a negative effect on current consumption through an increase in precautionary savings (Khan, 2008).

The ICAPM assumes that investors trade continuously and maximize their expected utility of lifetime consumption. It states that besides the market risk, the risk of unfavorable shifts in the investment opportunity set, as approximated by the changes of the state variables, will induce additional risk premiums and should be compensated[20]. In other words, investors will seek to hedge against not only shocks to wealth as in the traditional CAPM, but also against shocks to future investment opportunities. As specified by Dotsis (2015), investors will bid up the prices of assets that do well when future investment opportunities are expected to deteriorate, and consequently lower their expected returns. These assets command a smaller risk premium because they increase the investor's ability to hedge against unfavorable changes in investment opportunities. On the other hand, investors will require a higher premium for holding assets that do badly when future investment opportunities worsen.

The main difference between ICAPM and traditional CAPM is the additional state variables that acknowledge the fact that investors hedge against changes in the future investment opportunity set. The ICAMP is a linear factor model with wealth and state variables that forecast changes in the distribution of future returns or income (Cochrane, 2005).

In this study, the discrete-time version of the ICAPM is assumed to account for the cross-sectional asset returns. Following Campbell (1996) who suggest using innovations in state variables to forecast the changes in the future investment opportunity set, instead of using the state variables directly for the empirical implementation of the ICAPM, we consider the innovations of state variables that capture uncertainty about future investment opportunities in this research. According to ICAPM, both the excess market return and innovations in state variables that forecast changes in the future investment opportunity set should show up as pricing factors in the cross-section of asset returns.

We assume the unconditional expected returns can be expressed in the frame of ICAPM as follows:

[20] Campbell (1993) extends Merton (1973)'s model to a discrete-time ICAPM and derives a simple non-consumption based model with two risk factors: the unexpected current period return on the market portfolio, and news about future expected returns on the market portfolio.

$$E\left(R_{i,t}\right)-R_{f,t}=\beta_{i,m}\left(\gamma_{m,t}\right)+\sum_{k=1}^{K}\beta_{i,\mu^{k}}\left(\gamma_{\mu^{k},t}\right),\ \forall i \tag{2.1}$$

where $E\left(R_{i,t}\right)-R_{f,t}$ is the excess return of asset *i*, $R_{f,t}$ is the risk-free rate of return, $\gamma_{m,t}$ is the market risk premium, $\gamma_{\mu^{k},t}$ is the risk price for innovations of state variable *k*. The β s are the coefficients that can be estimated through following TSR:

$$R_{i,t}-R_{f,t}=\alpha_{i,t}+\beta_{i,m}\left(R_{M,t}-R_{f,t}\right)+\sum_{1}^{K}\beta_{i,\mu^{k}}\left(\mu_{t}^{k}\right)+e_{i,t} \tag{2.2}$$

where $R_{i,t}-R_{f,t}$ is the excess return of asset *i* at time *t*, $R_{M,t}-R_{f,t}$ is the excess return of the market portfolio at *t*, and μ_{t}^{k} is the innovation of state variable *k* at time *t*.

The beta terms in equation (2.1) measure how much risk should be priced while the gamma terms measure the price of risk, with the excess market return and innovations of state variables as risk factors.

2.1.2 What are the proper candidates for the state variables?

The ICAPM suggests that we should use variables that forecast stock market returns as proxies for investment opportunities, however, it provides little guidance for identifying them. Thus what are the proper candidates for the state variables has raised many discussions. Theoretically, state variables should be factors that have predicting power of the future investment opportunity set. Empirically, numerous researchers have explored various candidates that for the most part, are macroeconomic variables that related to business cycle fluctuations.

Fama (1981), Fama (1990), Geske and Roll (1983), and Schwert (1990) document that U.S. stock returns are positively related to the future growth rate in the gross national product (GNP)[21]. Stock and Watson (1989) find interest rates are particular useful predictors of future economic activity. Later, Brennan et al. (2004) develop and test a model assumes that the investment opportunity set is completely described by real interest rate and the maximum Sharpe ratio. The estimated real interest rate and Sharpe ratio both show strong business cycle-related variation and both state variables have significant risk premium in the cross-sectional asset test. Liew and Vassalou (2000) suggest to use the return on a

[21] Mullins and Wadhwani (1989) report a similar relationship in Germany and the United Kingdom.

market portfolio, dividend yield, short-term interest rates, term spreads, growth in the Gross Domestic Product (GDP) and the industrial production as indicators for the business cycle.

Other studies that identify significant predictors of the equity risk premium include: Lintner (1975), the interest rate; Campbell and Shiller (1988) and Fama and French (1988), the market dividend yield; Fama and French (1989), the term spread and the junk bond yield spread; Kothari and Shanken (1997), the book-to-market ratio; Dumas and Solnik (1995) exchange risk.

Among the attempts to find the economic variables that are able to help explain expected asset returns, Fama and Schwert (1977) prove that common stock returns associated with expected and unexpected components of the inflation rate[22]; Jagannathan and Wang (1996) include the return on human capital (using labor income growth as a proxy) as a new factor in addition to market beta; Campbell (1996) also find the future labor income growth a significant priced factors in determining excess stock returns; while Parker and Julliard (2005) and Hansen et al. (2005) examine the relationship between expected asset returns and the future consumption.

Chen et al. (1986) explore series of economic state variables related to industrial production, inflation (change of Consumer Price Index), risk premium (the spread between high- and low-grade bonds), term structure (the spread between long and short interest rate), consumption, etc., and examine whether innovations in those macroeconomic variables help explain the cross-section of average returns on NYSE stocks. They find several of these economic variables were found to be significant in explaining expected stock returns, variables related to industrial production, risk premium, term structure, and, somewhat more weakly, variable related to inflation.

Similarly, Keim and Stambaugh (1986) show that default spread and term spread forecast stock and bond returns. Moreover, Chen (1991) also confirm that the default spread, the term spread, the one-month T-bill rate, the lagged industrial production growth rate, and the dividend-price ratio are important determinants of future stock market returns. However, Li (1997) implement tests of ICAPM using forecasting variables (a yield spread measuring term premium, a yield spread for default risk, the dividend yield, one-month T-bill rate and the lagged market return) as risk factors; the evidence rejects the hypothesis that the forecasting variables are the risk factors that explain the time-series and cross-sectional variation in expected stock returns.

[22] See also researches on inflation: Shi et al. (2015), Adams et al. (1999), Bottazzi and Corradi (1991) on Italy market.

Ferson and Harvey (1991) strengthen the evidence that the predicted variation of asset returns is related to their sensitivity to the economic variables through the analysis of a group of six economic variables. Results turn out that the premiums associated with interest rate, term structure shifts, and default spreads are the important variables for capturing the predictable variation of asset returns in addition to the market risk premium.

Furthermore, Campbell (1987), Campbell (1991), Campbell and Shiller (1988a), Fama and French (1988), Fama and French (1989), Harvey (1989) and Kothari and Shanken (1997), have proposed various candidates related to the yield curve shape and aggregate dividends. For instance, Campbell (1987) document that the term structure of interest rates predicts excess stock returns in U.S.; Campbell (1991) shows that the unexpected stock returns are related to changes in expected future dividends or expected future returns. Kothari and Shanken (1997) provide evidence that B/M ratio and dividend yield are related to time-series variation in expected stock returns during the period 1926 to 1991.[23] Fama and French (1989) use three variables to forecast returns, which are dividend yield on the value-weighted NYSE portfolio, the default spread defined as the difference between yield on a portfolio of 100 corporate bonds and yield on a portfolio of bonds with Moody's Aaa ratings, and the term spread between the yield on the Aaa corporate bond portfolio and the one-month T-bill rate.

Inspiring by those findings and as Fama and French (1993, 1995, 1996) had themselves suggested that their SMB and HML factors could be interpreted as proxies for state variables which describe time variation in the future investment opportunity set in the context of Merton's ICAPM.[24] Furthermore, one of the macroeconomic explanations behind the success of FF3F Model is based on the time-varying investment opportunities, FF two factors SMB and HML are proxy for state variables. Many types of research are proceeded by relating the FF factors to macroeconomic variables that are closely related to business cycle fluctuations. Numerous empirical evidence in the literature suggests that the size factor SMB and value factor HML indeed carry information about future investment opportunities.

For choosing variables that have forecasting power for future investment opportunities, Fama (1991), Campbell (1996) have pointed out that ICAPM should not be used as only

[23] Many studies have found dividend yield to have predictive power in both cross-section Litzenberger and Ramaswamy (1979) and time series Rozeff (1984), Fama and French (1988), Fama and French (1989), and Campbell and Shiller (1988b).

[24] Simpson and Ramchander (2008) provide evidence that the FF3 model outperforms the standard CAPM in its ability to capture surprises related to various macroeconomic indicators.

criteria for selecting factors. Only factors that forecast future investment opportunities should be included in the model.

Both Liew and Vassalou (2000) and Vassalou (2003) report that FF factors SMB and HML convey significant information about future GDP growth not present in the market portfolio. Especially, Liew and Vassalou (2000) provide evidence by using data from ten developed countries. Vassalou (2003) find that when news related to future GDP growth presented in the asset pricing model, SMB and HML lose much of their explanatory power in the cross-sectional variation of average asset returns. Hanhardt and Ansotegui Olcoz (2008) found that this result extends to twelve countries of the Eurozone.

Prior study of Chan et al. (1985) explore multifactor pricing equation that consists of five economic variables to explain the firm size effect. The five variables are (1) the change in the state of the economy measured by the growth rate of industrial production; (2) the change in expected inflation; (3) the difference between the realized inflation rate; (4) the change in the long term rate measured by the difference between the return of a portfolio of long-term government bonds and the T-bill rate; (5) the changing risk premium measured by the behavior of bonds of different perceived riskiness. Among those economic variables, a measure of the changing risk premium and a measure of the changing state of the economy explained a large portion of the size effect.

Xing (2008b) claims that FF value factor HML may approximate by an investment growth factor defined as the difference in returns between low-investment stocks and high-investment stocks. Campbell and Vuolteenaho (2004), Brennan et al. (2004) and Petkova and Zhang (2005) all show that the value premium is correlated with innovations in their measures of investment opportunities.

Fama and French (1993) examine two bond-market factors TERM (the difference between the long-term government bond return and one-month T-bill rate) and DEF (the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return) as measures of unexpected changes in interest rates and the likelihood of default separately. They confirm that the tracks of both factors show up clearly in the time-series variation of stock returns. They also find both factors capture common variation in stock and bond returns when they are examined alone in the bond market or the stock market.

Both term spread and default spread are well known to forecast aggregate stock market returns (Fama and French (1989), Fama and French (1993) and Keim and Stambaugh (1986)). Term spreads and default spreads have been shown to have time series predictive ability to forecast stock market returns (Fama and French (1988), Stock and Watson

(1989)), so they are also widely used as potential conditioning variables in cross-sectional tests.

Hahn and Lee (2001, 2006) emphasize in their articles that since term spread and default spread are two of the most widely used proxies for future interest rates and time-varying risk premium separately, they are likely to capture well the hedging concerns to investors associated with variations in interest rates and risk premium. The authors choose both term spread and default spread as proxies for SMB and HML and specify a three-factor model in which the factors are the excess market return, changes in the default spread (Δdef) and changes in the term spread (Δterm). They conclude that Δdef and Δterm capture most of the systematic risks proxied by the FF factors SMB and HML in both time-series and cross-sectional dimensions (Δdef is proxy for size factor while Δterm proxy for B/M factor), and in the presence of Δdef and Δterm, FF factors are superfluous in explaining the size and B/M effects.

Following Campbell's (1996) argument that instead of relying on choosing important macroeconomic variables as empirical implementations of ICAPM, the factors that are related to innovations in state variables which forecast future investment opportunities should be considered in the model. Researchers like Campbell and Vuolteenaho (2004), Petkova (2006), In and Kim (2007) and Aretz et al. (2010) implement their research with innovations of state variables rather the economic variables themselves.

Petkova (2006) chooses a set of four innovations of state variables, including the short-term T-bill rate, term spread, aggregate dividend yield and default spread instead of some important macroeconomic variables. And she comes to a conclusion that FF factors SMB and HML are significantly correlated with innovations in state variables that describe investment opportunities and a model which uses innovations in SMB and HML and in the predictive variables explains the cross-sectional average returns better than the FF3F model. As a result, the author concludes that Fama-French factors proxy for innovations in predictive variables. More specifically, she denotes that HML proxies for a term spread surprise factor in returns, while SMB proxies for a default spread surprise factor.

Using the same set of four state variables as Petkova (2006), In and Kim (2007) adopt a new approach of wavelet analysis and examine to what extent FF factors SMB and HML share information with the innovations of state variables that describe investment opportunities. It is found that SMB and HML seem to play only a limited role in capturing alternative investment opportunities in the short run, but they share much information with alternative investment opportunities in the long run.

More recently, Aretz et al. (2010) consider a series of innovations of state variables that include innovations in economic growth expectations, inflation, the aggregate survival probability, the term structure of interest rates, and the exchange rate. They prove that most of the macroeconomic factors considered are priced, and B/M ratio, size and momentum capture cross-sectional variation in exposures to those macroeconomic factors. Specifically, the authors show B/M conveys useful information about term structure risk and economic growth, and size conveys information about default risk and term structure risk.

However, there are researchers deduce different conclusions, the ability of macroeconomic state variables to predict portfolio excess returns and the significance of factor loadings in TSRs are not encouraging. For instance, Campbell's (1996) own results are mixed. In his paper, he argued that CAPM ignores time variation in expected stock returns and the fact that human capital is also an important component of wealth, but still a good approximate model of stock and bond pricing in some limited senses.

Chen (2002) develop a model with time-varying expected market returns and time-varying market volatilities to reflect the changes in the investment opportunity set. The author examines the size effect, value effect and momentum effect but neither the value effect nor the momentum effect can be explained using changes in the investment opportunity set. Thus the author concludes that accounting for the changes in the investment opportunity set does little in explaining the cross-section of stock returns.

Shanken and Weinstein (2006) and Lewellen et al. (2010) express rather pessimistic views. The former re-examine the five macroeconomic factors studied by Chen et al. (1986) and Chan et al. (1985). Contrary to the previous literature, the authors show that only the industrial production factor is significantly priced in the overall period 1958 to 1983; the bond return premium, a highly significant factor in the earlier studies, is insignificantly negative for the whole period. The five factors only account for about 25% or 30% of the time-series variation in 20 size portfolio returns and the authors fail to find the evidence of factor pricing over the sub-period 1968 to 1977. In the latter article, the authors review the models suggest new risk factors to help explain expected returns (growth in macroeconomic output and investment and innovations in state variables included), which seem to do a good job explaining the size and B/M effects. They critique the empirical methods used in the literature and offer improving empirical tests and find that several models do not work as well as originally advertised.

Especially, on the contrary to Petkova (2006), Lioui and Poncet (2011) find that the method that used to make innovations in predictive variables is rather arbitrary, and loadings on innovations of state variables are rarely significant when tested on the 25-portfolios sorted by size and B/M equity. These innovations of state variables have extremely limited explanatory power in both time-series and cross-section regressions when extending the portfolio universe to include 30 industry portfolios. They also concluded that there is no proof that the FF factors proxy for time-varying investment opportunities, and the explanatory power of innovations on SMB and HML is almost inexistent in time-series and marginal in cross-sections, while SMB and HML themselves remain as significant as in the FF3F Model.

More recently, Boons (2016) find that a series state variables such as the default spread, the term spread, the short-term T-bill rate, robustly forecast macroeconomic activity. However, they find that FF factors SMB and HML are unable to drive out the risk premiums of those state variables and their underlying characteristics are able to do so only partially.

2.1.3 Evidence from outside of the U.S. market

Though the conflict point of views on whether macroeconomic variables are able to explain expected stock returns, the evidence that stock prices tend to fluctuate with economic news is supported by numerous empirical literatures. For instance, the early studies of Fama (1981), Fama (1990), Chen et al. (1986), Schwert (1990), and Ferson and Harvey (1991) have found that macroeconomic variables have explanatory power for U.S. stock returns. While this observation is not found only in U.S., such as Asprem (1989), Beckers et al. (1992), Ferson and Harvey (1993) and Cheung et al. (1997). have reached a similar conclusions using data of other international market out of U.S.

Asprem (1989) investigates the relations between stock indices, asset portfolios and macroeconomic variables in ten European countries. The results show that changes in stock prices are correlated to some measures of real economic activity, in particular positive related to future industrial production, exports, the yield curve in the U.S.; and negatively related to employment, the exchange rate, imports, inflation and interest rates. The author suggests these economic variables may be representatives of state variables in the ICAPM.

Hanhardt and Ansotegui Olcoz (2008) discuss the economic rationale of FF factors SMB and HML in Eurozone market in the context of Merton's (1973) ICAPM. The authors also extend their research by including a momentum factor of Carhart (1997) WML, and they test to what extent the profitability of the factors can be related to future economic growth measured by growth in the gross domestic product (GDP) in the Eurozone. Their results document that only the size factor SMB seems to contain strong and robust information with respect to future growth in GDP, while they fail to find the same significance for HML and WML (there appears to be a positive but not significant relationship between HML and GDP growth,). Thus they conclude that at least SMB, and to some extent HML, may serve as state variable that predict future changes in the investment opportunity set in the context of ICAPM.

Docherty et al. (2013) provide an empirical analysis of whether empirical regularities (they denote the size, value and momentum premium as empirical regularities) previously identified in the Australian market are related to macroeconomic risk factors such that they may be considered as the state variables of Merton's (1973) ICAPM. The authors examine two groups of macroeconomic fundamentals in their paper. The first group are the state variables employed by Chen et al. (1986)[25], and the second group are a series of macroeconomic forecast variables shown in the prior literature to predict equity returns. They report that all three empirical regularities examined change with the business cycle (HML is negatively related to the business cycle while SMB and momentum factor has the positive direction). Their results support the contention that the empirical regularities may be explained as macroeconomic risk factors in the Australian stock market. The authors suggest that the three anomalies are correlated with innovations of those macroeconomic variables that describe future investment opportunity set.

Cheung et al. (1997) examine two potential sources of international real return variation: changes in expected future cash flows and changes in discount rates in 18 national stock markets, and the authors give evidence that the global economic variables that proxy for the two sources of return variation significantly capture large fraction of total variation of the international stock market returns.

Cheung and Ng (1998) investigate the relationship between stock market indexes and measures of aggregate economic variables (the real oil price, real output, real money supply, and real consumption) on five countries stock market (Canada, Germany, Italy, Japan, and the U.S.) by adopting the cointegration approach. The authors find evidence of long-run comovements between the returns on national stock indexes and measures of the country-specific aggregate economic real variables. They further explore an error correction model which provides incremental information about the variation of stock returns that not found in other measures of return variation such as dividend yields, default and term spreads, and future GNP growth rates.

[25] The authors examine all the state variables documented by Chen et al. (1986) except the default spread: unexpected inflation, changes in expected inflation, industrial production growth and the term spread. As the authors claim that the default risk spread is not included in their forecast model due to the illiquidity of Australian bond markets.

Charles et al. (2016) investigate the relationship between stock returns and a range of economic fundamentals including short-term interest rates, several financial ratios (dividend-price ratio, dividend yield, E/P ratio, dividend-payout ratio) and technical indicators (price pressure, change in volume) on international markets (16 Asia-Pacific and 21 European stock markets). They show that the financial ratios have the weak predictive ability for stock returns while the price pressure and the short-term interest rate appear to have strong predictive power for stock return.

In emerging market, Hosseini et al. (2011) examine the relationship between stock market indices and four macroeconomic variables (crude oil price, money supply, industrial production and inflation rate) in China and India. Their results indicate that there exists the link between four macroeconomic variables and stock market index in both long and short run in both countries.

Pramod Kumar and Puja (2012), Tripathi and Seth (2014) and Gaur et al. (2015) investigate the impact of selected macroeconomic variables on the performance of Indian stock market, all of them find significant relationship between stock price and the selected macroeconomic factors (such as industrial production, inflation, short-term interest rate, exchange rate). On Malaysia stock market, Siti Noorahayusolah (2011) find a series of macroeconomic factors (inflation, interest rates, money supply, and exchange rates) has a significant impact on stock market returns.

Liang (2013) and Liang and Willett (2015) provide evidence that the performance of Chinese stock market is related to both its domestic economic fundamentals, the policy-driven factors such as exchange rate and bank deposits and bank loans have strong impacts on stock performance. However, the real economic factors such as industrial production seem not as significant as the policy-driven factors in explaining Chinese stock returns.

The latest empirical study of Mu (2016) investigates the relationship between seven selected macroeconomic variables (interest rate, inflation, oil price, unemployment rate, industrial production index, money supply, and exchange rate) and the stock markets in the US, Germany, and Hong Kong. Both short-term and long-term relationships between macroeconomic variables and the stock markets are shown in all the three countries.

Plenty researchers confirm the ability of FF factors (at least the size factor SMB) in explaining average excess stock returns on Chinese stock market. We consider several special features of Chinese stock market, and examine FF3F Model using data on CNAS stock market. We provide evidence that FF3F Model explains time-series variation of average excess stock returns well, and there always exists size premium. Though there are researchers who find the relevance between the performance of Chinese stock market and the domestic economic variables, rare have examined whether the economic underpinning of FF factors are related to the economic fundamentals of Chinese stock market, which is what we are going to investigate in this study.

Following the framework of Petkova (2006), we choose the same set of four variables in this study – including aggregate dividend yield, short-term T-bill rate, term spread and default spread. Our choice is also consistent with the standpoint of Campbell (1996) that instead of choosing those important macroeconomic variables, variables which have forecasting power for future investment opportunities should be considered in the model. The four variables are choosen to relate two aspects of investment opportunities, the yield curve and the conditional distribution of asset returns, and all these variables have been frequently used among literature.

We apply the vector autoregressive (VAR) approach of Campbell (1996) in this study to obtain the innovation terms of selected state variables and examine the performance of innovations of predictive variables on CNAS Stock Market during December 2006 to May 2015. In addition, we also investigate whether innovations of selected variables have the proxy ability of FF factors in China.

This chapter proceeds as follows: Section 2 presents our data and the VAR process to extract innovations of state variables; the TSR results of the five comparing models are demonstrated in section 3; section 4 test the cross-sectional validation of the five models; finally, the conclusions and discussions are in the last section.

2.2 Innovations in predictive variables and Vector Autoregressive approach

2.2.1 State variables

We choose the same set of state variables as Petkova (2006) in addition to the FF factors in our empirical test: dividend yield (DIV), term spread (TERM), default spread (DEF) and one-month T-bill rate (RF), which are among the most common used economic variables in the literatures as illustrated previously. The four predictive variables are chosen to model two important aspects of the investment opportunity set, the yield curve and the conditional distribution of asset returns. "*The ICAPM dictates that the yield curve is an important part of investment opportunity set*" Petkova (2006), Litterman and Scheinkman (1991) indicate that the two most important factors driving the term structure of interest rates are its level and its slope. One-month T-bill rate and the term spread are to capture variations in the level and slope of the yield curve. Petkova (2006) points out that the conditional distribution of asset returns is also a crucial aspect of investment opportunity set in the context of ICAPM. And growing literature indicates that the conditional distribution of asset returns which are characterized by its mean and variance, varies over time. The aggregate dividend yield, the default spread, and interest rates are among the most generally identified variables by numerous literature. Table 2.1 lists a partial of papers that document the relationship between the performance of equity market and the four state variables that we are going to apply in the following research.

Table 2.1 List of papers that document time variation of excess asset return and the state variables they use

State Variables	Paper/ author
Dividend yield	Campbell and Shiller (1988a), Fama and French (1988), Fama and French (1989), Kothari and Shanken (1997), Chen (1991)
Term spread	Campbell (1987), Keim and Stambaugh (1986), Fama and French (1989), Chen et al. (1986), Chan, Chen, and Hsieh (1985), Chen (1991)
Default spread	Fama and French (1989), Chen et al. (1986), Chan, Chen, and Hsieh (1985), Chen (1991)
Short-term T-bill rate	Brennan et al. (2004), Fama and Schwert (1977), Stock and Watson (1989), Chen (1991)

In addition to FF factors SMB and HML, the four other state variables we selected on Chinese market are:

Aggregate Dividend yield (DIV) is the sum of dividends over the last 12 months, divided by the actual value of the market index. Our study focuses on CNAS Stock Market, so we take all the CNAS stocks (both Shanghai A-share Stock Market Index and Shenzhen A-share Stock Market Index) present value as the actual value of the market index.

Term spread (TERM) is the difference between the yields of a 10-year government bond and a 1-year government bond. We download Generic China 10Y Government Bond and Generic China 1Y Government Bond which fit the definition.

Default spread (DEF) is the difference between the yields of a long-term corporate Baa-rated bond and a long-term government bond. Mention that the Baa-rated bond is rated by Moody's rating system, which is not available in Chinese bond market through Bloomberg. Thus we compute the default spread as the difference between the yields of a long-term corporate bond index (China 10Y Corporate Bond) and a long-term government bond index (China 10Y Government Bond).

Short-term Treasury bill rate (RF) is generally the one-month Treasury bill rate or called risk-free rate which is a typically proxy for the return on a one-month Treasury bill. In China, we use one-month fixed deposit rate as the proxy for the risk-free interest rate.

Monthly value-weighted excess market returns (CNAS stock market, including both Shanghai A-share stock Market and Shenzhen A-share Stock Market), one-month deposit rate, aggregate dividend yields, and yields of government bonds and corporate bonds are obtained from Bloomberg from November 2006 to May 2015. Starting from November 2006 rather than 2004 (which is the starting year in Chapter 1), because the available data of 'Term Spread' from Bloomberg begins from November 2006. FF factors SMB and HML are constructed the same way using the six Size-B/P portfolios in Chapter 1.

2.2.2 Vector Autoregressive method

According to ICAPM, only the unexpected component of the state variable should command a risk premium. The unexpected component is normally we called innovations (or unexpected shocks to state variables). Instead of using the state variables themselves directly for the empirical implementation of the ICAPM, Campbell (1996) suggests using innovations in such state variables to forecast the changes in the future investment opportunity set.

To derive the innovations of state variables[26], in the article of Chen et al. (1986), the author proposes using a vector autoregressive model to derive the residuals of the state variables as the unanticipated innovations in the economic factors. Campbell (1991) also state that "*The resulting vector autoregressive (VAR) system can be used to calculate the impact that an innovation in the expected return will have on the stock price, holding expected future dividends constant*" Following Campbell (1996), Petkova (2006) also adopts the first-order vector auto-regression model to derive the innovations of the state variables in her model. All the studies observed significant risk premiums induced by innovations in the state variables.

The Vector Autoregressive (VAR) Model generalizes the univariate autoregressive model (AR model) by allowing for more than one evolving variable. What is more, the VAR

[26] There are other approaches to estimate the innovations of state variables: Brennan et al. (2004) assumed the Ornstein–Uhlenbeck process whereas Hahn and Lee (2006) use the simple changes of state variables.

model is one of the most successful, and easy to use models for the analysis of multivariate time series. As Zivot and Wang (2007) say that "*the VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting*".

Following Petkova (2006), we adopt the VAR approach proposed by Chen et al. (1986) and Campbell (1991) in this study. All variables in a VAR enter the model in the same way: each variable has an equation explaining its innovation based on its own lags and the lags of the other model variables. We write the excess market return as the first element of the vector z_t, the other elements are the state variables which proxy for changes in the investment opportunity set. The assumption is that the vector z_t follows a first-order VAR:

$$z_t = Az_{t-1} + u_t \tag{2.3}$$

where, z_t is a $k \times 1$ vector which has k time-series variables, and z_{t-1} is called the 1- lag of z_t, which has the one-period back observation of the variables in z_t. A is a $k \times k$ matrix which is known as the companion matrix of the VAR. The error term u_t is also a $k \times 1$ vector, and the residuals in u_t are the innovation terms that are regarded as the risk factors. Petkova (2006) underlines that "*these innovations are risk factors since they represent the surprise components of the state variables that proxy for changes in the investment opportunity set*".

The assumption that the VAR is first-order is not restrictive since a higher-order VAR can always be stacked into first-order (companion) form in the manner discussed by Campbell and Shiller (1988a).

2.2.3 Innovations in state variables

In our research, we define the first element of vector z_t (equation (2.3)) is the excess market return $R_{M,t} - R_f$, denoted as $R_{m,t}$, and the other elements following are dividend yield (DIV_t), term spread ($TERM_t$), default spread (DEF_t), one-month deposit rate or risk-free rate(RF_t) and two FF factors (SMB_t and HML_t). Thus we have a set of seven variables, consistent with (Campbell, 1991) and (Petkova, 2006), for simplicity, all variables in the vector z_t have zero means or have been demeaned. The first-order VAR is:

$$\begin{Bmatrix} R_{m,t} \\ DIV_t \\ TERM_t \\ DEF_t \\ RF_t \\ SMB_t \\ HML_t \end{Bmatrix} = A \begin{Bmatrix} R_{m,t-1} \\ DIV_{t-1} \\ TERM_{t-1} \\ DEF_{t-1} \\ RF_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \end{Bmatrix} + u_t \tag{2.4}$$

Where A is a 7×7 matrix, and u_t represents a 7×1 vector of innovations for each element in the state vector z_t. From u_t we extract six innovation series corresponding to the dividend yield, one-month T-bill rate, term spread, default spread, SMB and HML, which are denoted as IDIV, IRF, ITERM, IDEF, ISMB and IHML.

Campbell (1996) emphasizes that it is hard to interpret estimation results for a VAR factor model unless the factors are orthogonalized and scaled in some way. In his research, he orthogonal the innovations of the state variables to both excess market return and labor income. In Petkova's (2006) article, the author implements the similar way as Campbell: the residuals u_t are orthogonalized from the market return $R_{m,t}$, and scaled to have the same variance as the market return. Aretz, Bartram, and Pope (2010) orthogonalize the market return with respect to their other macroeconomic fundamentals in order to isolate the variation in market returns not attributable to the macroeconomic fundamentals.

Following Petkova, in this study, the innovations of state variables are orthogonalized to the market factor separately. Precisely, the innovation of excess market return remains unchanged, innovation of dividend yield IDIV is orthogonalized to the excess market return; similarly, then innovation of the one-month T-bill rate IRF is orthogonalized to market factor. We do in this way to the other innovations of state variables ITERM, IDEF, ISMB and IHML. The innovations of the state variables are not orthogonalized from each other because this could add noise through the arbitrary ordering of the variables Boons (2016).

2.3 Time-series evidence on Chinese A-share stock market

This section is to examine the performance of the innovations of state variables which proxy for the future investment opportunities on CNAS stock market, and whether FF factors are proxies for innovations of these predictive variables. And we make comparisons among models that contain different factors, involving TSRs on excess market return, innovations of four state variables and innovations of FF factors (Model 1); regressions on excess market return, innovations of four state variables and original FF factors (Model 2); regressions on excess market return and innovations of the four state variables (Model 3); regressions only on excess market return and innovations of FF factors IHML and ISMB (Model 4); and time-times regressions on the original FF3F Model (Model 5).

2.3.1 Fama-French factors and innovations of state variables

2.3.1.1 Statistics description

Table 2.2 represents the summary statistics of the original FF three factors, the four state variables, and their innovations during the period December 2006 to May 2015 (102 months) in China. The mean of innovations of state variables (IDIV, ITERM, IDEF, and IRF) and innovations of FF factors (ISMB and IHML) are all close to zero. Not surprising that the t- statistic of SMB is significant at 5% confidence level, however, neither the

Table 2.2 Summary statistics of FF factors, state variables and their innovations (December 2006-May 2015, 102 months)

This table presents the summary statistics of original FF three factors, the four state variables and their innovations. Sd error is the standard error, and S.D. is the standard deviation. $R_{m,t}$ is the excess market return.

	Mean	Sd error	t-stats	Median	S.D.	Variance	Kurtosis	Skewness
$R_{m,t}$	-0.0025	0.0094	-0.2662	0.0050	0.0945	0.0089	0.8995	-0.6524
SMB	0.0138	0.0040	3.4643	0.0173	0.0402	0.0016	2.8062	-0.8652
HML	-0.0024	0.0035	-0.6823	-0.0058	0.0352	0.0012	3.4058	0.5215
DIV	0.0153	0.0006	24.8090	0.0150	0.0062	0.0000	-1.0382	-0.1687
TERM	0.0101	0.0006	18.2947	0.0088	0.0056	0.0000	-0.7151	0.6089
DEF	0.0141	0.0003	43.9995	0.0145	0.0032	0.0000	1.7629	-0.9073
RF	0.0130	0.0005	28.0855	0.0136	0.0047	0.0000	-0.4566	-0.1460
IDIV	0.0000	0.0001	0.0000	-0.0001	0.0008	0.0000	4.0478	-0.1081
ITERM	0.0000	0.0002	0.0000	-0.0001	0.0022	0.0000	1.3729	0.4382
IDEF	0.0000	0.0001	0.0000	0.0000	0.0013	0.0000	0.6156	-0.1258
IRF	0.0000	0.0002	0.0000	-0.0003	0.0020	0.0000	2.8160	0.9862
ISMB	0.0000	0.0040	0.0000	0.0031	0.0399	0.0016	2.7858	-0.7851
IHML	0.0000	0.0034	0.0000	-0.0016	0.0342	0.0012	3.3387	0.3595

innovations of state variables nor the innovations of FF factors are significant. Meanwhile, all the four state variables have high t-value. The significant t-stats indicate the high possibility to be priced in equity returns.

Primarily, we perform regressions with the single innovation in addition to excess market return (the results are presented in Appendix D), in order to have the first glance of whether such small values of innovations related to the average excess stock returns. It is shown that among the four innovations of state variables, 23 out of 25 loadings on IDIV is significant at 5% confidence level and negatively related to stock returns; while none of the loadings on ITERM and none of the loadings on IDEF is significant or exhibit any significant systematic patterns related to size or B/P ratio. There are 11 out of 25 loadings on IRF that are significant, and it seems that the loadings are not related to size or B/P neither. It is probably that IDIV and IRF are able to capture variation in average excess stock returns, while the ITERM and IDEF probably not. Whether innovations are related to size or B/P ratio is not clear.

Table 2.3 shows the correlation matrix for all the risk factors which are demeaned FF three factors ($R_{m,t}$, SMB and HML), the innovations of state variables (IDIV, ITERM, IDEF, and IRF) and the innovations of SMB and HML (ISMB and IHML). Notably, SMB and HML are very highly correlated with their innovations with correlation coefficients 0.9943 between SMB and ISMB, 0.9720 between HML and IHML. Similarly, Petkova (2006) find the returns on FF factors are also very highly correlated with their respective innovations (the correlation

Table 2.3 Correlation coefficients among risk factors

This table presents the correlation coefficients among risk factors (FF three factors, innovations of state variables, and innovations of SMB and HML). FF three factors are all demeaned. The underlined numbers show the most highly correlated coefficients.

	$R_{m,t}$	SMB	HML	IDIV	ITERM	IDEF	IRF	ISMB	IHML
$R_{m,t}$	1								
SMB	0.0065	1							
HML	0.1926	-0.3495	1						
IDIV	0.0000	-0.2593	0.0360	1					
ITERM	0.0000	0.1557	-0.3077	0.0337	1				
IDEF	0.0000	0.0184	0.0424	-0.1224	-0.2755	1			
IRF	0.0000	-0.2288	0.2380	0.0686	-0.4842	0.1131	1		
ISMB	0.0000	<u>0.9943</u>	-0.3533	-0.2608	0.1566	0.0185	-0.2301	1	
IHML	0.0000	-0.3614	<u>0.9720</u>	0.0370	-0.3166	0.0436	0.2449	-0.3635	1

is 0.92 between SMB and ISMB, 0.90 between HML and IHML) in U.S., thus she suggests that "*the returns on the HML and SMB portfolios are good proxies for the innovations associated with these variables*". ITERM and IRF are also significantly correlated with the correlation coefficient -0.4842. The high correlation coefficients indicate the factors probably share common information in explaining equity returns.

Considering the absolute value, the correlation among other risk factors are relatively weak, still there are factors share common information to some extent, such as SMB and HML (-0.3495), SMB and IDIV (-0.2593), SMB and IRF (-0.2288), HML and ITERM (-0.3077), HML and IRF (0.2380). The correlation coefficients are almost close to zero between the excess market return $R_{m,t}$ and the innovations, from which we can infer that the innovations have no correlation to the market factor.

2.3.1.2 Relation between FF factors and innovations of state variables

To test whether Fama-French factors are proxies for innovations of state variables on CNAS stock market. First of all, we perform two types of TSRs: (1) regressions of SMB and HML respectively on market factor and innovations of state variables, (2) regressions of each innovation of the state variables on FF three factors. Results of the two types of TSRs are presented separately in Table 2.4 and Table 2.5, showing intuitively the relation among those risk factors.

We first examine the relationship between two FF factors (SMB and HML) and four innovations of state variables estimated from a VAR process, controlling for the market factor, using the following two regression equations:

$$\begin{aligned} SMB = a_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \varphi_{i,t} \end{aligned} \tag{2.5}$$

$$\begin{aligned} HML = a_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \varphi_{i,t} \end{aligned} \tag{2.6}$$

Table 2.4 reports the regression coefficients and corresponding t-stats of equation (2.5) and (2.6). Corresponding t-stats are in the parentheses below the regression coefficients, corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags.

Table 2.4 Estimated coefficients of SMB and HML from risk factor regressions

This table presents the regression results of two FF factors, SMB and HML, on the other risk factors (market factor and innovations of state variables). The adjusted R-square is represented in the last column. Three FF factors and four state variables are all demeaned, and the t-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. The sample period is from December 2006 to May 2015.

Regressions:

$$SMB = a_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF + \beta_{i,IRF} IRF + \varphi_{i,t}$$

$$HML = a_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF + \beta_{i,IRF} IRF + \varphi_{i,t}$$

	a_i	$\beta_{i,m}$	$\beta_{i,IDIV}$	$\beta_{i,ITERM}$	$\beta_{i,IDEF}$	$\beta_{i,IRF}$	$Adj.\ R^2$
SMB	0.0012	0.0028	-12.1704	1.6072	1.0019	-3.4078	0.0720
(t-stats)	(0.4096)	(0.0622)	(**-3.3173**)	(0.6044)	(0.3028)	(-1.6984)	
HML	0.0000	0.0717	1.4015	-4.1733	-1.0707	1.9352	0.1004
(t-stats)	(0.0074)	(1.4730)	(0.4380)	(**-2.0204**)	(-0.3876)	(1.3428)	

Regression results indicate that SMB is related only to the innovations of aggregate dividend yield (IDIV), while HML is related only to the innovation of term spread ITERM. Consistent with Hahn and Lee (2006) and Petkova (2006), the authors provide evidence that HML is related to a term spread factor. However, we do not find a relationship between SMB and a default spread factor on CNAS stock market as the authors demonstrated on U.S. stock market. Instead, we find a significant and negative relationship between SMB and IDIV. We suspect that SMB shares information with IDIV, while HML shares information with ITERM. However, the negative relation between HML and ITERM we found is contrary to Hahn and Lee (2006) and Petkova (2006)'s statement that the HML factor is positively related to the innovation of the term spread. The regression results show an insignificant relationship between the two FF factors and innovations of default spread IDEF, means that IDEF has no explanatory power for SMB or HML.

We next perform the TSRs of contemporaneous innovations of state variables on FF three factors:

$$\mu_t = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + \delta_{i,t} \tag{2.7}$$

where we denote μ_t as the innovations of the four state variables and the regression results are shown in Table 2.5. Consistent with what we observe from the last regressions, IDIV and SMB, ITERM and HML are negatively and significantly correlated. However, the new evidence shows that both SMB (negatively) and HML (positively) significantly related with the innovation of one-month T-bill rate IRF.

Table 2.5 Time-series regressions of Contemporaneous innovations of state variables on FF factors

This table presents time-series regressions' results of innovations of four state variables on FF three factors. The adjusted R-squared is represented in the last column and in percentage value. Three FF factors and four state variables are all demeaned, and the t-statistics presented below the coefficients are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags. The sample period is from December 2006 to May 2015.

Regression: $\mu_t = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + \delta_{i,t}$

	a	*b*	*s*	*h*	*Adj. R^2*
IDIV	0.0000 (0.0878)	0.0001 (0.0631)	-0.0057 (**-2.1284**)	-0.0015 (-0.4699)	4.24
ITERM	-0.0000 (-0.0135)	0.0014 (0.6146)	0.0028 (0.4466)	-0.0192 (**-2.9789**)	7.30
IDEF	0.0000 (-0.0122)	-0.0002 (-0.1216)	0.0013 (0.3391)	0.0021 (0.4608)	2.73
IRF	0.0000 (0.0499)	-0.0008 (-0.3148)	-0.0082 (**-2.2742**)	0.0108 (**2.4572**)	5.39

Our findings of HML and ITERM is consistent with Hahn and Lee (2006) who provide evidence that HML is related to a TERM factor and Petkova (2006) who also find that ITERM covaries significantly with HML return. Furthermore, they also provide evidence of a relationship between SMB and DEF factor (or innovations of DEF), which seems not the case in our study. Inconsistent with Petkova, we find both SMB and HML are significantly related to IRF, none of FF factors are significantly related to IDEF.

The results from both types of regression suggest that FF factors might be related to the innovations of state variables, and it is reasonable to examine whether FF factors are proxies of innovations of state variables on CNAS stock market.

2.3.2 Time-series regressions and results

Following the two-step estimation approach developed by Fama and MacBeth (1973). In the first step, the TSRs are performed on each of 25 value-weighted Size-B/P portfolios. In this chapter, the TSRs are performed according to each model (five models) with 102 months (December 2006 to May 2015) data of CNAS stock market. We compare five different factor models, in each model, excess portfolios returns are regressed on different risk factors. The innovations are obtained from a VAR (1) process.

$$R_{i,t} - R_f = \alpha_{i,t} + \beta_{i,m}\left(R_{M,t} - R_f\right) + \sum_{1}^{n} \beta_{i,j} R_{j,t} + e_{i,t} \tag{2.8}$$

where, $R_{i,t} - R_f$ is the excess portfolios return at time t, $R_{M,t} - R_f$ is the excess return on the market portfolio at the time t, $R_{j,t}$ are the risk factor (innovations to the state variables and FF factors) at time t, $\beta_{i,j}$ are the regression coefficients.

2.3.2.1 *Five comparative models and time-series regressions*

The five TSR models are:

Model 1

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \beta_{i,ISMB} ISMB + \beta_{i,IHML} IHML + e_{i,t} \end{aligned} \tag{2.9}$$

Model 2

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + \beta_{i,SMB} SMB + \beta_{i,HML} HML + e_{i,t} \end{aligned} \tag{2.10}$$

Model 3

$$\begin{aligned} R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF \\ + \beta_{i,IRF} IRF + e_{i,t} \end{aligned} \tag{2.11}$$

Model 4

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,ISMB} ISMB + \beta_{i,IHML} IHML + e_{i,t} \tag{2.12}$$

Model 5

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,SMB} SMB + \beta_{i,HML} HML + e_{i,t} \tag{2.13}$$

The dependent variables in the five models are the 25 value-weighted Size-B/P portfolios we constructed in Chapter 1, which remains unchangeable in the regressions. Model 1 represents TSRs of the 25 value-weighted Size-B/P portfolios on excess market return, innovations of state variables and innovations of FF factors SMB and HML (ISMB and IHML). Similarly, Model 2 represents TSRs on excess market return, innovations of state variables and the original FF factors SMB and HML. The independent variables in Model 3 are excess market return and four innovations of state variables. In Model 4, the independent variables are excess market return and innovations of SMB and HML, Model 5 is nothing but the original FF3F Model.

We perform the TSRs of each model during the period December 2006 to May 2015 (102 months), and the regression results are reported separately in Table 2.6, Table 2.7, Table 2.8, Table 2.9 and Table 2.10. The left-half part of each table shows the TSR loadings, the corresponding t-statistics are reported on the right-half part and are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator with five lags. At the end of each table, the adjusted R-square and the residual standard error are also reported. The numbers in bold indicate the statistical significance at the 5% confidence level.

The regression results of Model 1 are shown in Table 2.6, the market factor still has strong explanatory power for the average excess stock returns. Both innovations of SMB (ISMB) and HML (IHML) are important factors in capturing average excess stock returns, all the t-stats of loadings on ISMB are statistically significant, and almost half of loadings (10 out of 25) on IHML are significant. Specifically, the highest B/P quintile has the most (all five) significant t-stats, while none of the loadings of the median B/P quintile is significant. The significant t-stats are concentrated on the lower B/P portfolios, the higher B/P portfolios, and bigger size portfolios. What's more, consistent with our previous findings on SMB in Chapter 1, the slopes on ISMB are systematically related to size, within each B/P quintile, the loadings decrease as the size increases. The loadings on IHML are also systematically positively related to B/P ratio, the loadings increase within each size quintile as B/P ratio increases, except the portfolio which has the smallest size and lowest B/P ratio.

As to the four innovations of state variables IDIV, ITERM, IDEF and IRF, only IDIV has several slopes that are significant (4 out of 25), none of other innovations have revealed the relationship with stock returns. Furthermore, none of the loadings on the innovations have shown a relationship with size or B/P ratio according to our results. Though the adjusted R-squared are relatively high (with averaged adjusted R-square 0.9018), which means that the average excess portfolio returns are well explained by Model 1, the majority of statistically significant of intercepts indicate that the average excess portfolio returns cannot fully explained by Model 1.

Table 2.6 Time-series regression on innovations of state variables and innovations of FF factors (period: December 2006-May 2015)

This table represents the time-series regression results of FF 25 value-weighted Size-B/P portfolios, the independent variables are market factor, innovations of four state variables and innovations of FF factors. The left-hand part shows the regression coefficients and adjusted R-square, and the right-hand part are the t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags and the residual standard error. Across rows are the five B/P portfolios and across the columns are the five size portfolios. Numbers in bold indicate statistical significance at 5% confidence level.

Model 1: $R_{i,t}-R_f=\alpha_i+\beta_{i,m}(R_{M,t}-R_f)+\beta_{i,IDIV}IDIV+\beta_{i,ITERM}ITERM+\beta_{i,IDEF}IDEF+\beta_{i,IRF}IRF+\beta_{i,ISMB}ISMB+\beta_{i,IHML}IHML+e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			α					$t(\alpha)$		
S	0.0179	0.0252	0.0228	0.0247	0.0227	**5.8834**	**9.3037**	**9.4438**	**8.4744**	**7.8648**
2	0.0154	0.0173	0.0159	0.0158	0.0154	**4.6410**	**5.6510**	**5.7802**	**5.5111**	**5.2831**
3	0.0115	0.0118	0.0120	0.0135	0.0128	**3.2843**	**4.5352**	**4.3679**	**4.4976**	**4.2713**
4	0.0098	0.0083	0.0087	0.0081	0.0065	**3.0528**	**2.8153**	**2.9950**	**2.3367**	**2.3341**
B	0.0074	0.0041	0.0022	0.0035	0.0033	**2.1024**	1.5132	0.6406	1.1473	1.2751
			β_m					$t(\beta_m)$		
S	1.0209	0.9876	0.9749	1.0120	1.0492	**21.3158**	**26.4098**	**29.5131**	**22.7772**	**29.0068**
2	1.0145	1.0152	1.0159	1.0338	1.0269	**25.6538**	**24.7389**	**25.3328**	**22.0610**	**22.7841**
3	1.0397	0.9861	1.0308	1.0607	1.0646	**14.3735**	**20.1119**	**25.5648**	**25.2300**	**24.4476**
4	0.9429	0.9847	1.0291	1.0863	1.0731	**17.6237**	**25.6068**	**20.1783**	**25.8298**	**23.6878**
B	0.9142	1.0668	1.1353	1.1351	1.0957	**15.9416**	**22.5296**	**21.9166**	**29.5371**	**27.3563**
			β_{IDIV}					$t(\beta_{IDIV})$		
S	3.2751	-2.3102	-0.8156	0.9441	0.0750	0.9032	-0.7082	-0.2985	0.3109	0.0302
2	-6.1561	-0.0931	-1.5454	-5.3985	-3.6960	-1.5625	-0.0273	-0.5056	-1.4915	-1.0674
3	-0.8919	-9.1442	-0.5226	-4.0396	-5.4912	-0.1786	**-2.5064**	-0.1589	-1.0313	-1.7678
4	-2.8806	-3.5185	-3.2334	-4.3813	-8.5200	-0.7883	-1.1344	-0.8728	-1.5061	**-3.0702**
B	-2.9095	-2.0242	-7.6830	-3.8872	-10.3291	-0.7797	-0.5854	**-2.6113**	-1.2754	**-3.3985**

Table 2.6 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			β_{ITERM}					$t(\beta_{ITERM})$		
S	-1.9340	-0.9496	-1.1513	-1.5466	-1.0292	-1.1306	-0.6686	-0.7425	-1.0023	-0.6187
2	-0.6318	-0.7727	-0.2835	-0.8363	-0.1556	-0.4437	-0.4202	-0.2186	-0.5192	-0.1068
3	-1.2174	0.4641	-1.2524	-0.7956	-1.3643	-0.5766	0.2940	-0.8213	-0.5121	-0.9311
4	-1.8504	-0.8149	-0.8775	-0.6636	-0.5776	-0.9658	-0.4176	-0.5017	-0.4357	-0.4730
B	-1.7075	-0.0352	-0.2197	0.4397	-0.8593	-0.8929	-0.0202	-0.1133	0.2686	-0.5058
			β_{IDEF}					$t(\beta_{IDEF})$		
S	0.8823	-0.9104	0.7130	0.5527	-1.4699	0.2669	-0.3571	0.3543	0.1896	-0.4381
2	-0.9837	-1.9387	-0.4241	1.0599	0.0827	-0.3012	-0.7744	-0.1785	0.4517	0.0353
3	1.4169	0.0828	-0.6519	-0.3042	-0.6642	0.4998	0.0310	-0.2938	-0.1304	-0.2579
4	-1.9631	-1.9086	-0.9741	-2.0648	1.7461	-0.6765	-0.6648	-0.4169	-0.6518	0.6922
B	1.8629	-1.1675	-0.4935	-1.4217	0.6514	0.6610	-0.5129	-0.1856	-0.6323	0.2943
			β_{IRF}					$t(\beta_{IRF})$		
S	0.0765	2.0675	-0.0315	1.6425	2.3907	0.0418	1.9204	-0.0285	1.1040	1.6245
2	-0.9933	2.0986	0.3137	0.2620	1.5061	-0.6139	1.3752	0.2821	0.1877	1.1568
3	0.4756	1.4246	-0.5305	0.9008	0.1893	0.2843	1.0858	-0.4079	0.6693	0.1185
4	-0.3925	0.0383	0.7621	2.0425	1.0622	-0.2931	0.0310	0.6112	1.0739	0.6892
B	-0.1263	1.7948	2.3551	1.2268	-1.2492	-0.1023	1.1507	1.5545	0.8016	-0.9919
			β_{ISMB}					$t(\beta_{ISMB})$		
S	1.7625	1.6844	1.6217	1.7152	1.6767	**12.7569**	**15.5231**	**16.0337**	**12.3844**	**13.5836**
2	1.3928	1.4495	1.5397	1.4481	1.5280	**10.2365**	**14.5667**	**13.1207**	**11.7784**	**11.6911**
3	1.3956	1.3037	1.3176	1.3120	1.2629	**8.5763**	**11.3764**	**11.7071**	**10.7589**	**10.7399**
4	0.9881	1.0498	1.0369	1.1262	0.9986	**7.4825**	**9.2700**	**8.2822**	**10.2948**	**7.3332**
B	0.3747	0.4433	0.3966	0.4695	0.3067	**2.8519**	**3.3169**	**2.5542**	**3.2099**	**2.3114**

Table 2.6 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
	β_{IHML}					$t(\beta_{IHML})$				
S	0.1362	-0.0439	0.0866	0.2263	0.3208	1.0111	-0.4074	0.9580	1.4900	**2.7936**
2	-0.1188	-0.0955	-0.0416	0.0654	0.5360	-0.7870	-0.8085	-0.3808	0.5474	**3.9935**
3	-0.3493	-0.2319	0.0153	0.2294	0.4681	-1.7781	-1.5900	0.1339	1.7504	**4.1131**
4	-0.5403	-0.3710	-0.1307	0.1838	0.5736	**-4.3947**	**-3.3734**	-1.0429	1.5094	**4.4155**
B	-0.8560	-0.4135	-0.0589	0.3556	0.9105	**-6.2358**	**-2.8479**	-0.3473	**2.2694**	**6.9503**
	Adj. R-square					Residual standard error				
S	0.8845	0.9306	0.9273	0.9088	0.9142	0.0424	0.0313	0.0313	0.0365	0.0359
2	0.9021	0.9090	0.9277	0.9100	0.9121	0.0370	0.0354	0.0318	0.0356	0.0349
3	0.8701	0.9020	0.9035	0.9053	0.9164	0.0444	0.0359	0.0360	0.0362	0.0336
4	0.8690	0.8967	0.8871	0.8954	0.9045	0.0393	0.0355	0.0378	0.0380	0.0353
B	0.8619	0.8920	0.8828	0.9057	0.9088	0.0374	0.0361	0.0395	0.0351	0.0341

Table 2.7 Time-series regression on innovations of state variables and FF factors, period: December 2006-May 2015

This table represents the time-series regression results of FF 25 value-weighted Size-B/P portfolios, the independent variables are market factor, innovations of four state variables and FF factors (SMB and HML). The left-hand part shows the regression coefficients and adjusted R-square, and the right-hand part are the t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags and the residual standard error. Across rows are the five B/P portfolios and across the columns are the five size portfolios. Numbers in bold indicate statistical significance at 5% confidence level.

Model 2: $R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF + \beta_{i,IRF} IRF + \beta_{i,SMB} SMB + \beta_{i,HML} HML + e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			α					$t(\alpha)$		
S	0.0157	0.0231	0.0207	0.0225	0.0206	**5.1651**	**7.8780**	**8.2215**	**7.4450**	**6.7707**
2	0.0137	0.0155	0.0140	0.0141	0.0134	**4.2324**	**5.2148**	**5.1658**	**4.9781**	**4.5902**
3	0.0098	0.0102	0.0104	0.0119	0.0112	**2.9827**	**3.8426**	**3.8791**	**4.0150**	**3.8731**
4	0.0086	0.0070	0.0075	0.0067	0.0052	**2.7561**	**2.4128**	**2.6434**	1.9065	1.8877
B	0.0069	0.0036	0.0017	0.0029	0.0029	**2.0604**	1.2857	0.4953	0.9615	1.1910
			β_m					$t(\beta_m)$		
S	1.0070	0.9867	0.9648	0.9906	1.0222	**18.8441**	**23.6717**	**26.7695**	**18.3013**	**24.5062**
2	1.0189	1.0185	1.0145	1.0256	0.9847	**21.8276**	**21.8706**	**22.0584**	**18.9804**	**18.8420**
3	1.0600	0.9997	1.0268	1.0404	1.0267	**12.6328**	**17.1738**	**22.6575**	**21.8938**	**20.6672**
4	0.9797	1.0078	1.0361	1.0696	1.0287	**17.0552**	**22.5750**	**18.4362**	**22.5940**	**19.4547**
B	0.9745	1.0946	1.1381	1.1080	1.0286	**16.1810**	**20.3107**	**18.8399**	**25.4167**	**21.6820**
			β_{IDIV}					$t(\beta_{IDIV})$		
S	3.3139	-2.4932	-0.9153	0.8616	0.0114	0.8356	-0.7328	-0.3381	0.2670	0.0039
2	-6.1348	-0.2314	-1.6289	-5.4936	-3.7849	-1.5570	-0.0650	-0.5194	-1.4663	-1.0420
3	-0.8089	-9.4098	-0.6392	-4.1060	-5.4866	-0.1633	**-2.4484**	-0.2017	-1.0900	-1.7971
4	-3.0447	-3.6051	-3.3329	-4.4353	-8.5388	-0.8477	-1.1314	-0.9357	-1.5256	**-3.3468**
B	-2.9486	-2.1363	-7.8680	-3.9625	-10.3656	-0.7906	-0.6095	**-2.6095**	-1.2874	**-3.5048**

Table 2.7 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			β_{ITERM}					$t(\beta_{ITERM})$		
S	-1.9810	-0.9542	-1.1701	-1.5072	-1.0541	-1.2324	-0.6413	-0.7889	-1.0040	-0.6426
2	-0.6175	-0.7760	-0.2606	-0.8462	-0.1644	-0.4141	-0.4033	-0.1948	-0.5104	-0.1106
3	-1.1817	0.4682	-1.2758	-0.7700	-1.3181	-0.5517	0.2794	-0.8090	-0.4772	-0.9178
4	-1.8697	-0.7666	-0.8908	-0.6319	-0.5493	-0.9516	-0.3839	-0.4903	-0.4003	-0.4291
B	-1.7003	0.0132	-0.1771	0.4690	-0.7978	-0.8758	0.0075	-0.0902	0.2802	-0.4679
			β_{IDEF}					$t(\beta_{IDEF})$		
S	0.8691	-0.9023	0.7136	0.5664	-1.4726	0.2717	-0.4030	0.3761	0.2102	-0.4831
2	-0.9813	-1.9325	-0.4143	1.0624	0.0850	-0.3198	-0.8341	-0.1896	0.4802	0.0384
3	1.4213	0.0972	-0.6516	-0.2947	-0.6534	0.5064	0.0371	-0.3041	-0.1316	-0.2669
4	-1.9594	-1.8927	-0.9723	-2.0545	1.7539	-0.7057	-0.6949	-0.4183	-0.6737	0.7012
B	1.8666	-1.1502	-0.4739	-1.4109	0.6680	0.6824	-0.5004	-0.1778	-0.6325	0.3002
			β_{IRF}					$t(\beta_{IRF})$		
S	0.1036	2.0274	-0.0470	1.6084	2.3858	0.0538	1.8046	-0.0411	1.1023	1.6519
2	-0.9939	2.0682	0.2857	0.2441	1.4892	-0.6161	1.4378	0.2604	0.1820	1.1181
3	0.4807	1.3623	-0.5481	0.8757	0.1725	0.2921	0.9731	-0.4220	0.6623	0.1114
4	-0.4226	-0.0002	0.7445	2.0178	1.0469	-0.3170	-0.0001	0.6285	1.0351	0.7011
B	-0.1380	1.7504	2.2963	1.1982	-1.2813	-0.1105	1.0989	1.4897	0.7897	-1.0832
			β_{SMB}					$t(\beta_{SMB})$		
S	1.7645	1.6685	1.6126	1.7092	1.6705	**13.2778**	**16.2937**	**16.1977**	**12.9987**	**13.9200**
2	1.3951	1.4375	1.5331	1.4396	1.5201	**10.7893**	**14.6810**	**13.8857**	**11.9651**	**12.5936**
3	1.4038	1.2810	1.3069	1.3070	1.2646	**8.8594**	**11.0313**	**12.3096**	**11.6093**	**12.0041**
4	0.9735	1.0438	1.0279	1.1225	0.9978	**7.5556**	**9.4158**	**8.4995**	**11.3355**	**7.9670**
B	0.3715	0.4351	0.3819	0.4638	0.3054	**2.8146**	**3.2339**	**2.4492**	**3.3447**	**2.4351**

Table 2.7 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			β_{HML}					$t(\beta_{HML})$		
S	0.1257	-0.0511	0.0786	0.2334	0.3125	0.8636	-0.4580	0.8007	1.4646	**2.5827**
2	-0.1145	-0.1009	-0.0386	0.0598	0.5309	-0.7393	-0.7904	-0.3439	0.4734	**3.9391**
3	-0.3375	-0.2397	0.0056	0.2336	0.4798	-1.6685	-1.5336	0.0470	1.7308	**4.1866**
4	-0.5506	-0.3618	-0.1373	0.1899	0.5801	**-4.2622**	**-3.0208**	-1.0487	1.5061	**4.5625**
B	-0.8555	-0.4051	-0.0544	0.3605	0.9247	**-5.9363**	**-2.6389**	-0.3089	**2.2640**	**7.2142**
			Adj. R-square					Residual standard error		
S	0.8900	0.9295	0.9285	0.9105	0.9165	0.0414	0.0316	0.0310	0.0362	0.0354
2	0.9051	0.9087	0.9286	0.9108	0.9137	0.0364	0.0354	0.0317	0.0355	0.0346
3	0.8738	0.8984	0.9037	0.9063	0.9197	0.0438	0.0366	0.0360	0.0360	0.0329
4	0.8687	0.8956	0.8871	0.8962	0.9067	0.0394	0.0357	0.0378	0.0378	0.0349
B	0.8632	0.8906	0.8816	0.9059	0.9126	0.0372	0.0363	0.0397	0.0350	0.0334

In Table 2.7, which reports the regression results of Model 2, we replace ISMB and IHML by the original FF factors SMB and HML, the other risk factors remain the same. The results are much like those of Model 1. It is not difficult to understand the similar results since SMB and HML are highly correlated to their innovations (refer to Table 2.3).

Table 2.8 displays the TSR results on innovations of four selected state variables in addition to excess market return (Model 3) over our sample period. Without FF factors or their innovations in the presence of regressions, IDIV plays an important role in capturing time-series variation of average excess returns with 23 out of 25 loadings are statistically significant at 5% confidence level (t-stats are corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags). Furthermore, the loadings on IDIV are all negative, within each B/P quintile, most of the loadings increase from smaller size portfolios to bigger size portfolios except the smallest size quintile, and the biggest size portfolios tend to have higher returns.

None of the loadings on ITERM or on IDEF is significant, only one out of 25 loadings on IRF is significant. However, consistent with Petkova (2006) that the loadings on ITERM are related to B/P ratio, within each size quintile, the higher B/P ratio portfolios tend to have smaller loadings, at least for the three higher B/P portfolios. Both Hahn and Lee (2006) and Petkova (2006) find the innovation of default spread is systematically related to size, though, we find no such a relationship between loadings on IDEF and firm size in this study. IRF seems to fluctuate with size, bigger size portfolios tend to have smaller loadings on IRF within each B/P quintile.

Comparing the adjusted R-squares of Model 1, Model 2 and Model 3, We notice that the adjusted R-square of Model 3 (with averaged adjusted R-square 0.7228) are much lower than those of Model 1 (with averaged adjusted R-square 0.9018) and Model 2 (with averaged adjusted R-square 0.9021), which indicate the lower descriptive power of Model 3, which contains only innovations of four state variables without FF factors (or innovations of FF factors).

Table 2.9 reports the TSR results on excess market return and innovations of SMB and HML (ISMB and IHML). Loadings on ISMB are all statistically significant at 5% confidence level and have an inverse relationship with size across each B/P quintile. Almost half of loadings on IHML (10 out of 25) are significant, and consistent with results of Model 1, the loadings are positively related to B/P ratio apart from the portfolio with the smallest size and lowest B/P ratio. The adjusted R-squares are all around 90% (with averaged adjusted R-square 0.9030).

Table 2.8 Time-series regression on innovations of state variables, period: December 2006-May 2015

This table represents the time-series regression results of FF 25 value-weighted Size-B/P portfolios, the independent variables are market factor, innovations of four state variables. The left-hand part shows the regression coefficients and adjusted R-square, and the right-hand part are the t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags and the residual standard error. Across rows are the five B/P portfolios and across the columns are the five size portfolios. Numbers in bold indicate statistical significance at 5% confidence level.

Model 3: $R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \beta_{i,ITERM} ITERM + \beta_{i,IDEF} IDEF + \beta_{i,IRF} IRF + e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			α					$t(\alpha)$		
S	0.0179	0.0252	0.0228	0.0247	0.0227	**3.3759**	**4.3212**	**4.2855**	**4.1337**	**4.0746**
2	0.0154	0.0173	0.0159	0.0158	0.0153	**2.8798**	**3.1962**	**2.9853**	**3.0231**	**2.8955**
3	0.0115	0.0118	0.0120	0.0135	0.0128	**2.1280**	**2.4358**	**2.5277**	**2.7405**	**2.7502**
4	0.0098	0.0083	0.0087	0.0081	0.0065	1.9630	1.7633	1.9847	1.6390	1.5922
B	0.0074	0.0041	0.0022	0.0035	0.0033	1.6861	1.1976	0.6040	1.0010	0.8332
			β_m					$t(\beta_m)$		
S	1.0209	0.9876	0.9749	1.0120	1.0492	**9.8737**	**10.7385**	**11.9462**	**10.7362**	**10.9240**
2	1.0145	1.0152	1.0159	1.0338	1.0269	**13.1740**	**12.4564**	**12.2129**	**12.2937**	**11.9734**
3	1.0397	0.9861	1.0308	1.0607	1.0646	**9.3296**	**11.7160**	**14.1004**	**14.4893**	**14.0225**
4	0.9429	0.9847	1.0291	1.0863	1.0731	**11.0381**	**13.6882**	**13.6469**	**15.2915**	**17.2509**
B	0.9142	1.0668	1.1353	1.1351	1.0957	**10.1041**	**15.7473**	**19.4823**	**24.9320**	**23.6765**
			β_{IDIV}					$t(\beta_{IDIV})$		
S	-17.9844	-22.8712	-20.4309	-19.6134	-19.8813	**-2.0760**	**-2.6197**	**-2.7405**	**-2.5233**	**-2.4337**
2	-23.2737	-17.8676	-20.3418	-22.9303	-21.5411	**-3.0490**	**-2.2935**	**-2.6387**	**-2.8917**	**-2.9174**
3	-18.3666	-25.3354	-16.5371	-19.6851	-20.2047	**-2.4629**	**-3.3987**	**-2.6421**	**-3.4911**	**-3.4613**
4	-15.6639	-16.8155	-16.0357	-17.8299	-19.8692	**-2.3220**	**-2.6005**	**-3.1312**	**-3.4911**	**-4.7184**
B	-8.6693	-7.9993	-12.5921	-9.1024	-12.7861	-1.5932	-1.9900	**-3.4977**	**-2.4445**	**-2.8244**

Table 2.8 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			β_{ITERM}					$t(\beta_{ITERM})$		
S	0.3304	1.9408	1.0936	0.2657	0.3266	0.0724	0.4942	0.2776	0.0649	0.0772
2	2.1025	1.9554	2.3645	1.2180	0.0632	0.6040	0.6455	0.6404	0.3923	0.0203
3	2.4832	3.5273	0.8015	0.3557	-1.2881	0.6216	1.0322	0.2751	0.1340	-0.4928
4	1.9927	2.4208	1.3345	0.3795	-1.3664	0.6967	0.8356	0.6054	0.1596	-0.7351
B	2.4672	2.4032	0.6637	-0.2899	-4.1661	1.0137	1.4308	0.4201	-0.2156	-1.7841
			β_{IDEF}					$t(\beta_{IDEF})$		
S	2.5025	0.8242	2.2451	2.0290	-0.1335	0.4632	0.1414	0.4629	0.4119	-0.0252
2	0.5390	-0.3841	1.1631	2.4408	1.0397	0.1119	-0.0807	0.2429	0.5707	0.2581
3	3.1892	1.6373	0.6519	0.7647	0.0999	0.6292	0.3601	0.1576	0.1926	0.0268
4	-0.3945	-0.4595	0.2047	-1.1332	2.1325	-0.1019	-0.1073	0.0605	-0.2711	0.6828
B	3.1549	-0.2805	-0.0330	-1.3321	-0.0161	0.9075	-0.1004	-0.0128	-0.5574	-0.0055
			β_{IRF}					$t(\beta_{IRF})$		
S	-5.6662	-3.7575	-5.3902	-3.7645	-2.7022	-1.8233	-1.0569	-1.7737	-1.1558	-0.8596
2	-5.9695	-3.0257	-5.0135	-4.5460	-2.6636	-1.8999	-0.8930	-1.7084	-1.5258	-1.0902
3	-4.9562	-3.4668	-4.9910	-3.1261	-3.2084	-1.5812	-1.1563	-1.8576	-1.2471	-1.4731
4	-4.8055	-4.2573	-3.0243	-1.4397	-1.2308	**-2.1350**	-1.6505	-1.3672	-0.5494	-0.6474
B	-3.0597	-0.5163	0.8896	0.3151	-0.5325	-1.4298	-0.2571	0.5533	0.1940	-0.2992
			Adj. R-square					Residual standard error		
S	0.6034	0.6311	0.6478	0.6313	0.6604	0.0786	0.0722	0.0689	0.0734	0.0713
2	0.6877	0.6760	0.6755	0.6973	0.6906	0.0660	0.0667	0.0675	0.0654	0.0655
3	0.6480	0.6901	0.7159	0.7369	0.7618	0.0731	0.0639	0.0618	0.0603	0.0567
4	0.6856	0.7266	0.7538	0.7710	0.8019	0.0609	0.0577	0.0559	0.0562	0.0508
B	0.7397	0.8422	0.8661	0.8825	0.8471	0.0514	0.0436	0.0422	0.0391	0.0442

Table 2.9 Time-series regression on innovations of FF factors, period: December 2006-May 2015

This table represents the time-series regression results of FF 25 value-weighted Size-B/P portfolios, the independent variables are market factor and innovations of FF factors. The left-hand part shows the regression coefficients and adjusted R-square, and the right-hand part is the t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags and the residual standard error. Across rows are the five B/P portfolios and across the columns are the five size portfolios. Numbers in bold indicate statistical significance at 5% confidence level.

Model 4: $R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,ISMB} ISMB + \beta_{i,IHML} IHML + e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			α					$t(\alpha)$		
S	0.0179	0.0252	0.0228	0.0247	0.0227	**5.8570**	**9.1204**	**9.6651**	**8.7478**	**7.9806**
2	0.0154	0.0173	0.0159	0.0158	0.0154	**4.6173**	**5.7955**	**5.7843**	**5.5248**	**5.2366**
3	0.0115	0.0118	0.0120	0.0135	0.0128	**3.3790**	**4.2925**	**4.4080**	**4.5435**	**4.1679**
4	0.0098	0.0083	0.0087	0.0081	0.0065	**3.0289**	**2.7980**	**3.0563**	**2.2689**	**2.1847**
B	0.0074	0.0041	0.0022	0.0035	0.0033	**2.1748**	1.4854	0.6195	1.1330	1.2000
			β_m					$t(\beta_m)$		
S	1.0209	0.9876	0.9749	1.0120	1.0492	**20.4422**	**23.2634**	**28.1865**	**21.1957**	**26.2015**
2	1.0145	1.0152	1.0159	1.0338	1.0269	**22.4253**	**22.7165**	**24.1228**	**18.9534**	**20.1681**
3	1.0397	0.9861	1.0308	1.0607	1.0646	**13.6161**	**16.1596**	**25.1005**	**22.5499**	**21.2923**
4	0.9429	0.9847	1.0291	1.0863	1.0731	**16.6857**	**23.0171**	**18.7585**	**22.5114**	**18.6476**
B	0.9142	1.0668	1.1353	1.1351	1.0957	**14.7199**	**20.9350**	**18.0653**	**26.6419**	**20.0845**
			β_{ISMB}					$t(\beta_{ISMB})$		
S	1.7388	1.6770	1.6245	1.6927	1.6518	**13.0825**	**14.7265**	**16.3813**	**12.2473**	**12.8010**
2	1.4338	1.4281	1.5447	1.4764	1.5367	**10.1991**	**13.8343**	**13.1178**	**10.9691**	**11.7009**
3	1.3954	1.3464	1.3208	1.3254	1.2887	**9.3564**	**10.0790**	**12.2018**	**11.2270**	**11.1690**
4	1.0006	1.0653	1.0457	1.1303	1.0400	**7.4170**	**8.6293**	**8.5051**	**10.0121**	**7.4292**
B	0.3904	0.4387	0.4205	0.4813	0.3756	**2.9629**	**3.4108**	**2.5686**	**3.3733**	**2.4881**

Table 2.9 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
	β_{IHML}					$t(\beta_{IHML})$				
S	0.1717	-0.0009	0.1117	0.2744	0.3640	1.2480	-0.0076	1.1739	1.7731	**3.0342**
2	-0.1098	-0.0613	-0.0310	0.0956	0.5617	-0.6870	-0.4863	-0.2801	0.7446	**4.0172**
3	-0.3156	-0.2106	0.0334	0.2606	0.5041	-1.5762	-1.4259	0.2884	1.9343	**4.0999**
4	-0.5081	-0.3532	-0.1021	0.2217	0.6140	**-4.0710**	**-3.2319**	-0.8287	1.7259	**4.4300**
B	-0.8153	-0.3924	-0.0176	0.3636	0.9314	**-5.8388**	**-2.7476**	-0.1015	**2.3487**	**6.5998**
	Adj. R-square					Residual standard error				
S	0.8875	0.9313	0.9296	0.9103	0.9153	0.0419	0.0312	0.0308	0.0362	0.0356
2	0.9041	0.9107	0.9305	0.9117	0.9144	0.0366	0.0350	0.0312	0.0353	0.0344
3	0.8743	0.9016	0.9070	0.9078	0.9177	0.0437	0.0360	0.0354	0.0357	0.0333
4	0.8727	0.8998	0.8906	0.8970	0.9033	0.0388	0.0350	0.0372	0.0377	0.0355
B	0.8645	0.8951	0.8832	0.9083	0.9064	0.0371	0.0356	0.0394	0.0346	0.0346

The TSR results of Model 5 (the original FF3F Model) in Table 2.10 are extremely like those of Model 4 (Table 2.9), FF3F Model still explains the time-series average excess returns well on CNAS stock market during December 2006 to May 2015. All the t-stats of loadings on excess market return and SMB are highly significant, and 10 out of 25 loadings on HML are significant as well, the adjusted R-squared are all around 90%, similar as those in Table 2.9. However, the majority of significantly intercept continues indicate that the average excess stock returns on CNAS stock market cannot fully capture by FF3F Model.

2.3.2.2 Brief comparison and summary

Comparing Model 1 and Model 2, the difference is that we include innovations of FF factors (ISMB and IHML) or FF factors themselves (SMB and HML) in addition to excess market return and innovations of state variables. The results tell no remarkable differences between the TSRs of the two models. It is revealed that FF factors and their innovations have approximately the same explanatory power for stock returns on CNAS stock market.

Comparing Model 3 with Model 2 (or Model 1), the regression results suggest that the regression model contains only the innovations of state variables without FF factors (or their innovations) as independent variables dramatically reduce the explanatory power of the model. The connections between innovations and size or B/P ratio (IDIV and size, ITERM and B/P ratio, and IRF and size) disappear when the regressions are performed with FF factors (or their innovations). Furthermore, in the presence of FF factors (or their innovations), the innovations of state variables - especially IDIV - seem not able to explain time-series variation of expected stock returns.

Comparing Model 4 with Model 1 and Model 5 with Model 2, including innovations of state variables or not in the regression model do not change the performance of FF factors (innovations of FF factors) in capturing time-series variation of expected stock returns. The innovations of state variables that describe time variation in investment opportunities have little or marginal effect when adding them into FF3F Model or model with innovations of FF factors as independent variables. Comparing Model 4 and Model 5, the results prove again the high correlation between FF factors and their innovations, since the regressions results are much alike from both models.

We can conclude that FF factors (or innovations of FF factors) explain the time-series variation of expected stock returns well, with or without the innovations of state variables are included in the model. When the four innovations of state variables are regressed alone,

Table 2.10 Time-series regression on FF3F model, period: December 2006-May 2015

This table shows the time-series regression results of FF 25 value-weighted Size-B/P portfolios on FF3F model. The left-hand part shows the regression coefficients and adjusted R-square, and the right-hand part are the t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator with five lags and the residual standard error. Across rows are the five B/P portfolios and across the columns are the five size portfolios. Numbers in bold indicate statistical significance at 5% confidence level.

Model 5: $R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,SMB}SMB + \beta_{i,HML}HML + e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			α					$t(\alpha)$		
S	0.0158	0.0232	0.0207	0.0226	0.0207	**5.1197**	**7.5733**	**8.4139**	**7.5664**	**6.7025**
2	0.0136	0.0156	0.0140	0.0140	0.0134	**4.2131**	**5.2460**	**5.1461**	**4.9841**	**4.5060**
3	0.0098	0.0101	0.0104	0.0119	0.0112	**3.0746**	**3.6019**	**3.9167**	**4.0346**	**3.7754**
4	0.0086	0.0070	0.0075	0.0067	0.0052	**2.7130**	**2.3837**	**2.6843**	1.8375	1.7431
B	0.0069	0.0036	0.0017	0.0029	0.0028	**2.1252**	1.2625	0.4714	0.9402	1.1059
			β_m					$t(\beta_m)$		
S	1.0045	0.9837	0.9630	0.9873	1.0192	**18.6519**	**20.8981**	**25.2693**	**17.5126**	**23.0016**
2	1.0182	1.0161	1.0138	1.0234	0.9828	**18.9259**	**20.4411**	**21.1811**	**16.3995**	**16.7307**
3	1.0577	0.9981	1.0255	1.0382	1.0242	**12.0269**	**13.9348**	**22.5043**	**19.2727**	**17.8041**
4	0.9773	1.0066	1.0341	1.0670	1.0259	**16.2656**	**20.6871**	**17.1025**	**19.5467**	**15.5571**
B	0.9716	1.0932	1.1352	1.1075	1.0271	**14.8421**	**18.9966**	**15.4809**	**22.7688**	**16.5446**
			β_{SMB}					$t(\beta_{SMB})$		
S	1.7402	1.6623	1.6158	1.6876	1.6460	**13.4101**	**14.8754**	**16.2425**	**12.6110**	**12.8491**
2	1.4354	1.4172	1.5389	1.4680	1.5291	**10.4139**	**13.5197**	**13.4322**	**10.8677**	**12.2027**
3	1.4029	1.3250	1.3107	1.3207	1.2901	**9.5778**	**9.6442**	**12.4894**	**11.7651**	**12.0529**
4	0.9867	1.0599	1.0372	1.1269	1.0387	**7.3400**	**8.5896**	**8.5953**	**10.6518**	**7.8389**
B	0.3871	0.4315	0.4069	0.4762	0.3738	**2.9199**	**3.3151**	**2.4676**	**3.4661**	**2.5677**

Table 2.10 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			β_{HML}					$t(\beta_{HML})$		
S	0.1616	-0.0090	0.1034	0.2797	0.3554	1.0902	-0.0784	1.0136	1.7539	**2.8807**
2	-0.1062	-0.0674	-0.0289	0.0893	0.5561	-0.6579	-0.5031	-0.2588	0.6766	**4.0611**
3	-0.3054	-0.2195	0.0237	0.2635	0.5139	-1.5122	-1.4237	0.2018	1.9478	**4.2881**
4	-0.5189	-0.3457	-0.1092	0.2262	0.6186	**-4.0547**	**-2.9736**	-0.8671	1.7360	**4.6804**
B	-0.8159	-0.3856	-0.0152	0.3674	0.9433	**-5.6547**	**-2.5790**	-0.0865	**2.3783**	**6.9345**
			Adj. R-square					Residual standard error		
S	0.8927	0.9303	0.9308	0.9119	0.9175	0.0409	0.0314	0.0305	0.0359	0.0352
2	0.9070	0.9104	0.9313	0.9123	0.9159	0.0360	0.0351	0.0310	0.0352	0.0341
3	0.8778	0.898	0.9071	0.9088	0.9209	0.0431	0.0367	0.0353	0.0355	0.0327
4	0.8723	0.8988	0.8905	0.8978	0.9055	0.0388	0.0351	0.0373	0.0375	0.0351
B	0.8657	0.8938	0.8819	0.9086	0.9100	0.0369	0.0358	0.0397	0.9086	0.0339

only IDIV has explanatory power for average return; while in the presence of FF factors (or innovations of FF factors), IDIV loses its capability in capturing time-series variation of expected stock returns. FF factors contain the information of innovations of aggregate dividend yield (IDIV) on CNAS stock market over our research period. In the next section, we will perform the CSRs among the comparing five models, and examine whether innovations of state variables have explanatory power in cross-section variation of excess stock returns, furthermore, whether FF factors proxy for the innovations of state variables in the cross-section.

2.4 Cross-sectional validation of five comparing models

In this section, following Petkova (2006), we examine cross-section validation that FF factors proxy for innovations of state variables on CNAS stock market over our sample period. The objective is to test whether an asset's loadings with respect to these risk factors are important determinants of its average return.

In the second pass of Fama and MacBeth's approach, the CSRs are performed by regressing the portfolios' excess returns on the estimated betas obtained from the first step of Fama-MacBeth's two-stage approach, for a given date.

$$R_{i,t} - R_f = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \sum_{1}^{n} \gamma_j \hat{\beta}_{i,j} + \varepsilon_{i,t} \tag{2.14}$$

where, the independent variables, $\hat{\beta}$s are the loadings which have been estimated from the TSRs and stand for exposures to the corresponding risk factor. γs are the coefficients of the CSRs and stand for the reward for bearing the risk of that factor ('price of risk' or 'risk premium'). "*If loadings with respect to innovations in a state variable are important determinants of average returns, then there should be a significant price of risk associated with that state variable*"[27].

As documented in Chapter 1, the Fama and MacBeth (1973) two-stage approach has the classical Errors-in-variables (EIV) problem, thus, we also report Shanken (1992)'s adjusted t-stats (SH t-stats) in the CSRs.

[27] Petkova (2006)

Considering our research, for each month, we regress the excess returns of 25 Size-B/P portfolios on the estimated betas that are obtained from the TSRs in the previous section. Since we have 102 months over our sample period (December 2006 to May 2015), 102 CSRs have been performed using OLS regressions, then the regression constants and the coefficients have been averaged over the 102 estimations.

We perform the cross-section regressions of five models corresponding to the five time-series models we have examined in the previous section:

Model 1#

$$\begin{aligned} R_{i,t} - R_f = &\gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{IDIV} \hat{\beta}_{i,IDIV} + \gamma_{ITERM} \hat{\beta}_{i,ITERM} + \gamma_{IDEF} \hat{\beta}_{i,IDEF} + \gamma_{IRF} \hat{\beta}_{i,IRF} \\ &+ \gamma_{ISMB} \hat{\beta}_{i,ISMB} + \gamma_{IHML} \hat{\beta}_{i,IHML} + \varepsilon_{i,t} \end{aligned} \tag{2.15}$$

Model 2#

$$\begin{aligned} R_{i,t} - R_f = &\gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{IDIV} \hat{\beta}_{i,IDIV} + \gamma_{ITERM} \hat{\beta}_{i,ITERM} + \gamma_{IDEF} \hat{\beta}_{i,IDEF} + \gamma_{IRF} \hat{\beta}_{i,IRF} \\ &+ \gamma_{SMB} \hat{\beta}_{i,SMB} + \gamma_{HML} \hat{\beta}_{i,HML} + \varepsilon_{i,t} \end{aligned} \tag{2.16}$$

Model 3#

$$R_{i,t} - R_f = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{IDIV} \hat{\beta}_{i,IDIV} + \gamma_{ITERM} \hat{\beta}_{i,ITERM} + \gamma_{IDEF} \hat{\beta}_{i,IDEF} + \gamma_{IRF} \hat{\beta}_{i,IRF} + \varepsilon_{i,t} \tag{2.17}$$

Model 4#

$$R_{i,t} - R_f = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{ISMB} \hat{\beta}_{i,ISMB} + \gamma_{IHML} \hat{\beta}_{i,IHML} + \varepsilon_{i,t} \tag{2.18}$$

Model 5#

$$R_{i,t} - R_f = \gamma_0 + \gamma_m \hat{\beta}_{i,m} + \gamma_{SMB} \hat{\beta}_{i,SMB} + \gamma_{HML} \hat{\beta}_{i,HML} + \varepsilon_{i,t} \tag{2.19}$$

$R_{i,t} - R_f$ are the same 25 Size-B/P portfolios as in the TSRs, and for each model, the estimated betas are obtained from the TSRs of the corresponding model (for example the estimated betas in Model 1# are the TSR coefficients of Model 1). Model 1# is the CSR on the loadings of excess market return, four innovations of state variables and innovations of FF factors. Model 2# represents the CSR on the loadings of excess market return, four innovations of state variables and FF factors. Model 3# represents the CSR on the loadings of excess market return and four innovations of state variables. Model 4# is the CSR of market factor and innovations of SMB and HML, while Model 5# is nothing but the CSR of FF3F Model.

The CSRs results of the five models are reported in Table 2.11. Across the rows we report the regressions coefficients and the corresponding t-statistics below each coefficient. The adjusted R-squares are reported in the last column. The numbers in bold indicate statistical significance at the 5% confidence level. We analyze the results by comparing the models:

- Comparing Model 1# and Model 2#, the loadings on exposure to market factor $\hat{\beta}_m$ (with FM t-stats -2.9752 in Model 1# and -3.0838 in Model 2#) and exposure to the innovation of one-month T-bill rate $\hat{\beta}_{IRF}$ (with FM t-stats 2.2365 in Model 1# and 2.3197 in Model 2#) are statistically significant in both models no matter regress with exposure to FF factor or their innovations. However, under the EIV correction, the significance of t-stats only exists for market factor. ISMB in Model 1# and SMB in Model 2# are both significantly priced, robust to the EIV adjustment; while the exposures to IHML or HML are not significant variables in the cross section. None of the exposures to innovations of state variables is significantly priced in explaining the cross-sectional excess portfolios' returns adjusted to EIV problem. The results show that whether we regress innovations of state variables with SMB and HML (or with ISMB and IHML) does not change the empirical outcomes.

  The very similar results obtained from Model 4# and Model 5# prove again that the FF factors (SMB and HML) and their innovations (ISMB and IHML) make no big difference between the CSR results. The market factor and ISMB are priced in Model 4#, correspondingly, the market factor and SMB are significantly priced in Model 5#. It is noteworthy that Model 5# is exactly the CSR of the original FF3F Model, the market beta is an important determinant in explaining the cross-sectional variation of the excess portfolio returns during the period December 2006 to May 2015, and the estimated coefficient of the loadings on market beta is negative (-0.0334) with FM t-stats -2.1285 and Shanken adjusted t-stats is -3.3191. Consistent with previous findings, size factor SMB is positively significantly priced and value factor HML still remains not significantly priced in the cross section of portfolio returns. This finding indicates that the ability of market factor and SMB in capturing cross-sectional variation of stock returns is robust at least over our research periods[28].

[28] We examine the cross-sectional validation of FF3F Model on Chinese A-share stock market during July 2004 to May 2015, and we find that there exists market premium and size premium over this sample period.

Table 2.11 Cross-sectional regressions of five comparative models

This table reports the Fama-MacBeth cross-sectional regressions using excess returns of 25 Size-B/P portfolios on Chinese A-share stock market, the independent variables are the estimated loadings of time-series regressions from the first stage of Fama-MacBeth approach. We perform the cross-sectional regressions for the following five models:

Model 1#: $R_{i,t}-R_f=\gamma_0+\gamma_m\hat{\beta}_{i,m}+\gamma_{IDIV}\hat{\beta}_{i,IDIV}+\gamma_{ITERM}\hat{\beta}_{i,ITERM}+\gamma_{IDEF}\hat{\beta}_{i,IDEF}+\gamma_{IRF}\hat{\beta}_{i,IRF}+\gamma_{ISMB}\hat{\beta}_{i,ISMB}+\gamma_{IHML}\hat{\beta}_{i,IHML}+\varepsilon_{i,t}$

Model 2#: $R_{i,t}-R_f=\gamma_0+\gamma_m\hat{\beta}_{i,m}+\gamma_{IDIV}\hat{\beta}_{i,IDIV}+\gamma_{ITERM}\hat{\beta}_{i,ITERM}+\gamma_{IDEF}\hat{\beta}_{i,IDEF}+\gamma_{IRF}\hat{\beta}_{i,IRF}+\gamma_{SMB}\hat{\beta}_{i,SMB}+\gamma_{HML}\hat{\beta}_{i,HML}+\varepsilon_{i,t}$

Model 3#: $R_{i,t}-R_f=\gamma_0+\gamma_m\hat{\beta}_{i,m}+\gamma_{IDIV}\hat{\beta}_{i,IDIV}+\gamma_{ITERM}\hat{\beta}_{i,ITERM}+\gamma_{IDEF}\hat{\beta}_{i,IDEF}+\gamma_{IRF}\hat{\beta}_{i,IRF}+\varepsilon_{i,t}$

Model 4#: $R_{i,t}-R_f=\gamma_0+\gamma_m\hat{\beta}_{i,m}+\gamma_{ISMB}\hat{\beta}_{i,ISMB}+\gamma_{IHML}\hat{\beta}_{i,IHML}+\varepsilon_{i,t}$

Model 5#: $R_{i,t}-R_f=\gamma_0+\gamma_m\hat{\beta}_{i,m}+\gamma_{SMB}\hat{\beta}_{i,SMB}+\gamma_{HML}\hat{\beta}_{i,HML}+\varepsilon_{i,t}$

For each model, the cross-sectional regressions are performed on each month (102 months) during the period December 2006 to May 2015, then the 102 constants and coefficients have been averaged. The first row within each model reports the regression coefficients (gammas), and the corresponding Fama-MacBeth (FM) t-stats and Shanken adjusted (SH) t-stats are reported in the brackets below the coefficients across the second row and third row, separately. Numbers in bold indicate statistical significance at 5% confidence level. The averaged adjusted R-squared are reported in the last column in percentage form.

Model	γ_0	γ_m	γ_{IDIV}	γ_{ITERM}	γ_{IDEF}	γ_{IRF}	γ_{ISMB}	γ_{IHML}	γ_{SMB}	γ_{HML}	Adj. R^2 (%)
Model 1#	0.0539	-0.0516	0.0003	-0.0001	0.0002	0.0012	0.0090	0.0048			
FM t-stats	(**3.5969**)	(**-2.9752**)	(1.8283)	(-0.1314)	(0.6759)	(**2.2365**)	(**2.1616**)	(1.2536)			56.22
SH t-stats		(**-4.9132**)	(1.2735)	(-0.0885)	(0.4741)	(1.6731)	(**2.0987**)	(1.1875)			
Model 2#	0.0560	-0.0534	0.0003	-0.0000	0.0002	0.0012			0.0088	0.0010	
FM t-stats	(**3.7506**)	(**-3.0838**)	(1.8186)	(-0.0297)	(0.6181)	(**2.3197**)			(**2.1219**)	(0.2678)	56.05
SH t-stats		(**-5.0751**)	(1.2436)	(-0.0196)	(0.4279)	(1.7166)			(**2.0600**)	(0.2481)	
Model 3#	0.0196	-0.0229	-0.0007	-0.0004	0.0005	-0.0008					
FM t-stats	(1.1463)	(-1.2504)	(**-2.9932**)	(-0.5596)	(1.3557)	(-1.2350)					46.66
SH t-stats		(**-2.1532**)	(**-2.0752**)	(-0.3679)	(1.0195)	(-1.0283)					

Table 2.11 Continued

Model	γ_0	γ_m	γ_{IDIV}	γ_{ITERM}	γ_{IDEF}	γ_{IRF}	γ_{ISMB}	γ_{IHML}	γ_{SMB}	γ_{HML}	Adj. R^2 (%)
Model 4#	0.0313	-0.0330					0.0118	0.0022			
FM t-stats	(**2.3868**)	(**-2.1064**)					(**2.8090**)	(0.5808)			52.01
SH t-stats		(**-3.2828**)					(**2.8039**)	(0.5827)			
Model 5#	0.0318	-0.0334							0.0117	-0.0002	
FM t-stats	(**2.4221**)	(**-2.1285**)							(**2.7876**)	(-0.0654)	51.99
SH t-stats		(**-3.3191**)							(**2.7877**)	(-0.0643)	

- Comparing Model 3# with Model 1# or Model 2# (we take the pair of Model 3# and Model 2# as example since the results of Model 1# and Model 2# are quite similar), when the CSRs are performed on the loadings of market factor and innovations of four state variables (Model 3#) eliminating SMB and HML (or ISMB and IHML), only loadings on excess market return and on IDIV is significantly priced (EIV adjusted). Never IDEF or ITERM or IRF has significant loadings in CSRs regardless of regressing with only innovations of state variables (Model 3#) or with FF factors (Model 2#). Especially, though the loading on IDIV is the only significant determinant of average returns, in the presence of FF factors or their innovations, the significance of loading on IDIV disappears. The information contained in IDIV seems totally captured by the market factor and size factor in explaining the cross-sectional variation of average portfolio returns.

- Comparing Model 4# with Model 1# and Model 5# with Model 2#, the analyze is much similar for both pairs of models, thus we take Model 5# and Model 2# for example. In Model 2#, none of the loadings on IDIV, ITERM, IDEF or IRF is important determinants of average returns; and the presence of innovations of the four state variables do not drive FF factors out.

- Comparing all the five models, inconsistent with Petkova (2006), the loadings on the excess market return are always negatively statistically significant on CNAS stock market, which suggest that there exists robust negative market premium. The exposures to ITERM, IDEF and IRF are not significant variables by all means in cross section (Petkova finds that loading of ITERM is a significant factor in the cross section of 25 portfolios). SMB or ISMB is an important determinant in explaining the variation of cross-sectional stock returns but HML or IHML is not; the existence of size premium and the lack of value premium are robust to the different research periods on CNAS stock market. In terms of the average adjusted R-square of the five models, it is obvious that Model 3# has the lowest one (46.66%). While the other models explain relatively a larger percentage of the cross-sectional variation in average returns of portfolios than Mode 3, in which the independent variables are only market excess return and innovations of state variables.

We summarize the findings of CSR in Table 2.11 and answering the questions proposed at the beginning of this section. The presence of the four innovations of state variables that forecast future investment opportunities does not drive FF factors out. The information contained in the innovation of aggregate dividend yields IDIV seems totally captured by the combination of market beta and SMB (or ISMB). Though the model involves both FF factors and innovations of state variables as risk factors performs slightly better than the original FF3F Model (considering the averaged adjusted R-square terms), FF factors might have played a limited role in capturing alternative investment opportunities proxied by innovations of state variables.

A supplement conclusion of Chapter 1: market beta and SMB are able to explain the cross-sectional variation of average stock returns except for the value factor HML over the period December 2006 to May 2015 on CNAS stock market. Furthermore, it seems that there exist robust negative market premium and positive size premium but no value premium on CNAS stock market, which is independent of research periods.

2.5 Conclusions

This paper investigates the explanatory ability of the innovations of four macroeconomic variables: aggregate dividend yield, one-month T-bill rate, term spread and default spread on CNAS stock market, using monthly data during the period December 2006 to May 2015 (102 months). To examine whether the innovations of the selected four predictive variables are able in capturing average excess stock returns in both time-series and cross-section, further whether FF factors SMB and HML proxy for the innovations of state variables that describe future investment opportunities on CNAS stock market, the TSRs and CSRs are performed on FF 25 Size-B/P portfolios on five comparing models separately.

Results from the TSR indicate that FF factors don't lose their explanatory power no matter when examined alone or in combination with innovations of state variables on CNAS stock market. When regressed alone, the innovations of selected state variables do not have the ability in capturing average stock returns except IDIV, which might indicate that the FF factors totally capture the information of IDIV in explaining time-series stock returns. Consistent with literature, we find innovation of term spread is related to B/P ratio, while inconsistently, we find no systematical relationship between innovation of default spread and firm size, instead, we find IDIV is related to size on CNAS stock market.

We conclude from the CSRs, the original FF factors (market beta and SMB) has ability in capturing the cross-sectional variation of excess stock returns and there are significant market risk premium and size premium during the period December 2006 to May 2015. Inconsistent with studies on U.S. stock market, in the presence of four innovations of state variables, FF factors do not lose their ability in capturing cross-sectional variations of excess stock returns on Chinese stock market. We find the information contained in the innovation of aggregate dividend yields (IDIV) seems totally captured by the combination of market beta and size factor. FF factors might have played a limited role in capturing alternative investment opportunities proxied by innovations of the selected four state variables. We may conclude that the innovations of the selected four state variables are not an essential element when we try to understand the average return on Chinese stock market. Thus, we propose to consider other economic variables in this case or trying to find other explanations of the success of FF factors in China.

Write between chapter 2 and chapter 3

The study in chapter 2 is based on one of the three specific theories that are most discussed – exposure to changes in economic variables in the context of ICAPM (the other two specific theories are distress risk, and asymmetric exposure to economic conditions). The three theories are not an exhaustive list of specific theoretical explanations for the performance of the FF3F Model. It represents three prominent theories that have empirical support.

As the results of chapter 2 suggested that FF factors do not lose their explanatory power in the presence of innovations of the four selected state variables (aggregate dividend yield, one-month T-bill rate, term spread and default spread) on CNAS stock market during the period December 2006 to May 2015. In other words, FF factors might not proxy for innovations of selected variables on CNAS stock market over the sample period.

In this case, we seek another theoretical explanation in the following chapter 3, which is the distress risk. Since one explanation for the persistent returns performance of high book-to-market stocks is the risk of financial distress, which can be found in an extensive literature. For instance, Chan and Chen (1991) argued that distressed firms are more sensitive to changes in economic conditions and documented that distressed firms, as proxied by dividend reductions and leverage, earned relatively high returns. Thus, they were able to provide an explanation as to why small firms earn high returns – these firms were more likely to have experienced dividend reductions and be highly leveraged. FF (1992) themselves showed that stocks with high book-to-market equity ratios earned relatively high returns, they proposed that this could be due to the decrease in market value associated with lower earnings prospects for those firms in distress. Furthermore, FF and other researchers continued to attribute the empirical evidence to distress risks in subsequent papers (Fama and French (1995; and Fama and French (1996)).

In addition, Firm's distress risk is an important indicator of a firm's performance and is also one of the most concerned characteristics by investors and firms. Measuring distress risk has been a hot research direction since the early 1930s FitzPatrick (1932). And two kinds of dominant models: accounting-based models that based on accounting ratios and market-based models that based on the market information are well developed and widely used in the massive of literature. The studies based on those predictive models are applied for investigating the relationship between distress risk and stock returns or comparing among the models. For instance, Dichev (1998), Griffin and Lemmon (2002), Vassalou and Xing (2004), Chava and Purnanandam (2010). all provide evidence that stock returns are related to distress risk (default risk).

One test of whether distress can explain why FF factors are priced risk factors was performed by Vassalou and Xing (2004). The researchers measured the default risk of individual stocks using a model developed by Merton (1974). Note that the risk of default is a relatively more extreme outcome of the risk of distress. The Merton's measure of default risk is the basis behind the credit ratings of Moody's KMV.

We carry out the following research and construct the distress risk factor using data of CNAS stock market during July 2005 to May 2015. To investigate whether FF factors proxy for distress risk on Chinese stock market, we augment FF3F Model with a mimicking distress risk factor. Furthermore, we implement both accounting-based and market-based model in estimating firms' distress risk to examine whether the different methods have effect on the empirical results.

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This chapter investigates the relationship between stock returns and distress risk, examine whether the size and value effects are related to distress risk on Chinese A-share stock market. Furthermore, we explore an augmented four-factor model by adding a distress risk factor in addition to Fama-French Three-Factor Model in order to examine whether Fama-French factors proxy for the distress risk. To measure the financial distress risk and construct distress risk factor, we apply both accounting-based model and market-based model, the comparisons are performed between the results obtained from the two different methods. Then Fama-MacBeth two-stage approach and Errors-in-Variables adjusted method are implemented to perform the regressions.

3.1 Financial distress risk

Financial distress, also known as default risk, financial crisis or financial failure, is the situation that a company has certain kind of financial difficulties, generally, it is defined as "the likelihood that a levered firm will not be able to pay the contractual interest or principal on its debt obligations" Garlappi et al. (2008). The worst situation of financial distress is bankruptcy, we say that the firm has gone into bankruptcy when a company reaches the point where it is unable to pay its debt and must stop its economic activity.

Beaver (1966) defines the firm's failure as the inability of a firm to pay its obligations as they mature and points out that financial distress occurs when any of the following events comes up: bankruptcy, bond default, an overdrawn bank account, or nonpayment of a preferred stock dividend.

Ross et al. (1998) summarized previous studies and concluded that financial distress contains four conditions: (1) business failure, that is, a company cannot pay the outstanding debt after liquidation; (2) legal bankruptcy, namely, a company or its creditors applies to the court for a declaration of bankruptcy; (3) technical bankruptcy, namely, a company cannot fulfill the contract on schedule to repay principal and interest; and (4) accounting bankruptcy, namely: a company's book net assets are negative[29].

While in China and some other developing countries, financial distress is usually defined as the certain degree of financial deterioration ruled by the national security management institution. For example, in China, a listed firm is defined as 'Special Treatment' (ST) by China Securities Regulatory Commission if (1) a listed firm has negative net profits for two years consecutively, (2) the shareholders' equity of the company is lower than the registered capital, and (3) a firm's operations have stopped and there is no hope of restoring operations in the next three months due to natural disasters, serious accidents or law-suit and arbitration. According to the Chinese regulation, if an ST firm cannot improve its performance within the next three years, it is labeled as 'Particular Transfer' (PT) and may be delisted from the stock exchange market[30].

None of the shareholders, creditors or investors is willing to witness the fail (bankruptcy) or deterioration of the firm since this situation make them suffer severe financial losses. So identifying firms that likely go into the deterioration situation in advance is of consequence. In China, firm's default risk is also one of the most concerned characteristics by investors and firms, many policymakers and financial institutions needs to improve their understanding of distress risk of Chinese firms. It is important to develop an early warning

[29] Sun et al. (2014)

[30] Geng et al. (2015)

system for prediction of firms' financial distress, which have been a hot topic over the years in China.

3.2 Measurement of financial distress risk

The primary question of predicting distress risk is how to measure it, and the financial distress prediction, or called bankruptcy prediction, acts as an important role in the decision-making of various areas, including accounting, finance, business, and engineering etc. The prediction of distress risk has experienced from the qualitative analysis to quantitative analysis, and along with the development of computer technology, the ANNA (Artificial Nerve Network Analysis) Model which based on the statistics method and computer, seems to be the new generation of a prediction model for distress risk. Our research focuses on the quantitative models of measuring distress risk, which is still the dominant methods in the research field of financial distress risk.

Early in 1932, FitzPatrick (1932) analyzes and compare the financial ratios of successful industrial firms and those of failed firms, and he finds the significant difference between the financial ratios of the two kinds firms. In addition, the author also points out that financial ratios can not only reflect the financial condition but also the business performance of a firm, what's more, the financial ratio has predict ability for the firm's future. Thereafter, among

Table 3.1 Classification of financial distress prediction models

Classification	Author	Method/Model
Accounting-based models	Beaver (1966)	Univariate Discriminant Analysis
	Altman (1968)	Multiple Discriminant Analysis
	Ohlson (1980)	Logit model
	Zmijewski (1984)	Probit model
Market-based models (Option-pricing theory)	Merton (1974)	Option-pricing model
	Crosbie and Bohn (2003)	KMV model
Market-based model (dynamic reduced-form model)	Shumway (2001)	Hazard model

numerous researches devote to predicting distress risk, the use of accounting ratios or market information are two dominant classifications. Later in recent years, there are models which consider both accounting and market information. Table 3.1 presents the dominating models in predicting financial distress since 1930'.

3.2.1 Accounting-based models

The accounting-based information is an important indicator of whether a company may encounter the financial distress or not, it can reflect a firm's financial conditions and business performance, and thus predict the future of the company. The early models to predict distress risk is mainly use accounting ratios.

The first study using a statistical approach to measure distress risk based on accounting information is Beaver (1966) univariate analysis of financial ratios which aims at predicting the corporate failure. Six groups[31] 30 ratios are selected and tested on 79 failed firms and 79 sound firms during 1954 to 1964. He performs a dichotomous classification test of the predictive ability of the chosen accounting measures and identifies the six most powerful ratios: cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratio, and no-credit interval. He found that those indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure. Beaver initiates 'The Univariate Discriminant Model' which make it easier for predicting finance distress using a simple model.

Despite the prominent step forward of Beaver in measuring and predicting default risk, the univariate model cannot comprehensively predict the distress risk of a firm, for instance, (1) single ratios calculated by Beaver do not capture time variation of financial ratios; (2) different accounting ratios may have different predicting ability and result in different consequences for the same firm; (3) there are interaction effects among different accounting ratios, single ratio is not able to capture multidimensional interrelationships within the firm. So that the interpretation of a single ratio in isolation may be incorrect. The weaknesses of Beaver's univariate model have led to the development of the multiple discriminant analysis which will be the subject of the following section.

[31] Cash-flow ratios, net-income ratios, debt to total-asset ratios, liquid-asset to total-asset ratios, liquid-asset to current debt ratios and turnover ratios

3.2.1.1 Altman's Z-score

To improve the accuracy of the assessment of distress risk from the univariate analysis, Altman (1968) apply a multiple discriminant analysis (MDA) to examine 66 manufacturing companies in the U.S., half of which filed bankruptcy while half of which are solvent between 1946 and 1965.

Similar as Beaver, 22 accounting ratios are selected on the basis of their popularity in the literature and their potential relevancy to the study, and are classified into five categories: liquidity, profitability, leverage, solvency, and activity. Finally, five variables are selected as doing the best job together to predict the corporate bankruptcy after applying the following processes:

(1) Observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable; (2) evaluation of inter-correlations between the relevant variables; (3) observation of the predictive accuracy of the various profiles; and (4) judgment of the analyst.

The five variables constitute the final discriminant function, which we call it Z-score:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \tag{3.1}$$

Where, Z is overall index (Z-score),

X_1 is Working capital/Total assets,

X_2 is Retained Earnings/Total assets,

X_3 is Earnings before interest and taxes/Total assets,

X_4 is Market value equity/Book value of total debts,

X_5 is Sales/Total assets.

The lower a firm's Z-Score, the higher its default probability (DP). Altman proposes the "cut-off" point (critical point) so that to predict at what level to bankruptcy a firm is according to its Z-score. It is concluded that firms which have a Z-score below 1.81 are all bankrupt; the firms having Z-score between 1.81 to 2.675 are defined in a "*gray area*" or "*zone of ignorance*", which means the firms are in a situation that is not so clear, they have the probability to bankrupt; while firms having a Z-score bigger than 2.99 clearly are in the non-bankrupt condition. Still, it is uncertain about a firm whose Z-score is in the "*zone of ignorance*", Altman obtains a critical Z value 2.675, which is to tell from the bankrupt and non-bankrupt firms in this area.

Altman's Z-score improves accounting-based techniques of the identification of financial distress risk, and it has advantages over Beaver's univariate model by considers a set of weighted combined accounting ratios. Altman proves that his model has an extremely accurate in predicting bankruptcy.

However, MDA has some well-known limitations. Such as (1) the statistical assumptions that predictors need to be normally distributed and the variance-covariance matrices of the predictors should be the same for both groups of firms (bankrupt and non-bankrupt); (2) the output of MDA model is a value (or score) which has little intuitive interpretation, since it is basically an ordinal ranking (discriminatory) device. (3) the accuracy of Altman's model two or three year prior to default drops drastically than the accuracy one year prior to default, the reason maybe that deteriorate of some accounting ratios is just the appearance instead of the essence of bankruptcy.

3.2.1.2 Ohlson's O-score

Ohlson (1980) criticizes the restrictive assumptions of Altman's MDA and comment that previous studies appear to have overstated the predictive power of models. To avoid the problem of MDA, Ohlson is the first who introduces the conditional logit analysis which is one of the conditional probability analysis to predict the probability of default and estimate firms' failure. The major advantage of the logit analysis is that *'no assumptions have to be made regarding prior probabilities of bankruptcy and/or the distribution of predictors'*.

The logit model is based on the cumulative distribution function to maximize the joint probability of default for the distressed firms and the probability of non-failure for the healthy companies in the sample. Similar to the MDA, this method weights the independent variables and assigns a score, however, this method estimates the probabilities of default for each company in a sample.

Suppose P as the probability of default for any given firm, let X_i denote the predictors for the i th observation, let W_i be the parameters of X_i, the expression of logit model is:

$$P = \frac{1}{1+e^{(-y_i)}} = \frac{1}{1+e^{-(W_0+W_1X_1+W_2X_2+\cdots+W_nX_n)}} \tag{3.2}$$

Doing a little transformation and we will have:

$$y_i = ln(\frac{P}{1-P}) = W_0 + W_1X_1 + W_2X_2 + \cdots + W_nX_n = \sum_{i=0}^{n} W_i \cdot \sum_{i=1}^{n} X_i \tag{3.3}$$

The logit model supposes that $ln(P/(1-P))$ can be explained linearly by accounting ratios. P is the probability function which value is between 0 and 1 ($0 \le P \le 1$)[32], the cutoff is 0.5, which means that if P bigger than 0.5, companies tend to have more probability of default, otherwise, the companies are healthy. Unlike the MDA which use a Z-score value to predict whether a firm is bankrupt or not, logit model uses a probability to measure the default risk, which makes it more accurate and reliable.

Ohlson chooses the sample that contains 105 firms which are bankrupt and 2058 non-bankrupt firms between the period 1970 and 1976, and all the firms are classified as an industrial. He constructs three logit models, model 1 predicts bankruptcy within one year, model 2 predicts bankruptcy within two years, and model 3 predicts bankruptcy within one or two years. The statistic "Percent Correctly Predicted" of the three models are 96.12%, 95.55%, 92.84% respectively.

He identifies four factors: the size of the company, a measure(s) of the financial structure, a measure(s) of performance and a measure(s) of current liquidity; which are statistically significant in affecting the probability of firm failure.

Finally, nine independent variables are employed to determine the probability of bankruptcy:

- SIZE = log (total assets / GNP price-level index)
- TLTA = total liabilities / total assets
- WCTA = working capital / total assets
- CLCA = current liabilities / current assets
- OENEG = 1 if total liabilities > total assets, 0 if otherwise
- NITA = net income / total assets
- FUTL = funds from operations / total liabilities
- INTWO = 1 if a net loss for the last two years, 0 otherwise
- CHIN = $(\text{net income}_t - \text{net income}_{t-1}) / (|\text{net income}_t| + |\text{net income}_{t-1}|)$

Assigning the corresponding weights to each variable and get the final O-score formula:

$$\begin{aligned} O = &-1.32 - 0.407\log(SIZE) + 6.03(TLTA) - 1.43(WCTA) + 0.076(CLCA) \\ &-1.72(OENEG) - 2.37(NITA) - 1.83(FUTL) + 0.285(INTWO) - 0.521(CHIN) \end{aligned} \tag{3.4}$$

In which, two of them are dummies (OENEG and INTWO). The use of qualitative variables is another advantage of the logit model compared to the discriminant analysis which is limited to the interpretation of quantitative ratios.

[32] Refer to McFadden and others (1973) for a comprehensive analysis of the logit model.

Contrary to Altman's Z-score, the lower a firm's Z-Score, the more likely of a firm encounter default, the probability of default positively changes with Ohlson's O-score, which means the higher the O-score the higher the default risk.

Ohlson's logit model have several advantages: the predictors do not need to follow the normal distribution or the same variance-covariance matrices rule, and unlike Altman's MDA of which the output is a value, the logit model is based on the conditional probability analysis and measures the firm's probability of default. come to the conclusion that the logit model generally is superior to the MDA approach of Altman. Kleinert (2014) compares the performance of three accounting-based models in Belgium and Germany and draw the conclusion that Ohlson's logit model performs most accurate. In the Asian market, Wang and Campbell (2010a) studied listed Chinese companies during 2000 to 2008 and report a high accuracy rate (95%) of Ohlson's model. Pongsatat et al. (2004) conclude that the Ohlson's logit model has a higher predictive ability in all three years preceding bankruptcy than that of Altman's MDA approach in Thailand.

Despite all the advantages, some critics are left on Ohlson's logit model: the use of maximum likelihood methodology to estimate the parameters makes the computational procedure complex. Hillegeist (2004) argues that Ohlson's logit model fails by not including time varying changes. Grice and Dugan (2001) emphasizes that the relation between financial ratios and their effects on bankruptcy changes over industries and time.

Ohlson himself gives advice that the choice of different accounting ratios could improve the likelihood function. However, he also suggests that such non-accounting information as equity prices or their volatility might be most useful and should be examined in future research. The use of non-accounting information for predicting financial distress has led to the development of a special class of default-risk models based on the value of a firm set by the market.

3.2.2 Market-based models

Since the prevalent of accounting-based models in modeling the default risk, there follows some criticism about the decline performance and limitation of using accounting variables to predict distress risk[33].

[33] Lev and Zarowin (1999), Mensah (1984), Hillegeist et al. (2004), Wu et al. (2010), Begley et al. (1996).

Several reasons are listed below to query the distress risk measures which are based on accounting data:

- Default probability is a prediction about the likelihood of future events, though accounting information is backward-looking. Accounting models use information derived from the financial statements which aim to measure past performance and may not be very informative in predicting the future status of the firm. As Hillegeist et al. (2004) argue that since the accounting statements are prepared on a going-concern basis, they are of limited utility in predicting bankruptcy by design.

- In addition, "the conservatism principle often causes asset values to be understated relative to their market values, particularly for fixed assets and intangibles. Downward-biased asset valuations will cause accounting-based leverage measures to be overstated." Hillegeist et al. (2004)

- Financial ratios vary substantially across industries. Thus, accounting-based coefficients are specific to the industry and sample used and cannot be generalized with respect to all firms in the market.

- Accounting-ratio-based models are typically built by searching through a large number of accounting ratios with the ratio weightings estimated on a sample of failed and non-failed firms. Since the ratios and their weightings are derived from sample analysis, such models are likely to be sample specific. An additional point of critics has been that accounting models ignore economic idiosyncrasies and that data are collected over many years while leaving out market changes Mensah (1984).

- Most importantly, another deficiency is that accounting-based models do not incorporate a measure of asset volatility. Volatility is a crucial variable in analyzing and predicting bankruptcy because it captures the likelihood that the value of the firm's assets will decline to such an extent that the firm will be unable to repay its debts.

Those limitations of models using accounting variables in modeling default risk bring on the models that rely on market information. The equity market contains an alternative and potentially superior source of information about default probability because it assembles information from other sources in addition to the financial statements.

There are two classes of models that based on market data, specifically, structural models Merton (1974) use option pricing methods to compute the default probability from the level and volatility of market value of assets, and reduced-form models[34] Shumway (2001) allow the default intensity to be extracted from debt or credit market securities. Since the vast majority of the market-based models are on the basis of option-pricing theory, we will mainly introduce the two popular model derived from option pricing theory and a model which belongs to the class of dynamic reduced-form models of default.

3.2.2.1 Black-Scholes and Merton (BSM) option-pricing model

Merton (1974) is the first who proposed a market-based model which applies the option-pricing methodology developed by Black and Scholes (1973) to relates the default risk to the capital structure of the company. In Merton's model, the equity (common stock) of a firm can be viewed as a standard European call option on the underlying firm's assets with a strike price equal to the book value of the firm's liabilities.

The limited liability feature of equity means that the equity holders have the right, but not the obligation, to pay off the debt holders and take over the remaining assets of the firm. That is, the holders of the other liabilities of the firm essentially own the firm until those liabilities are paid off in full by the equity holders. Thus, in the simplest case, equity is the same as a call option on the firm's assets with a strike price equal to the book value of the firm's liabilities Crosbie and Bohn (2003).

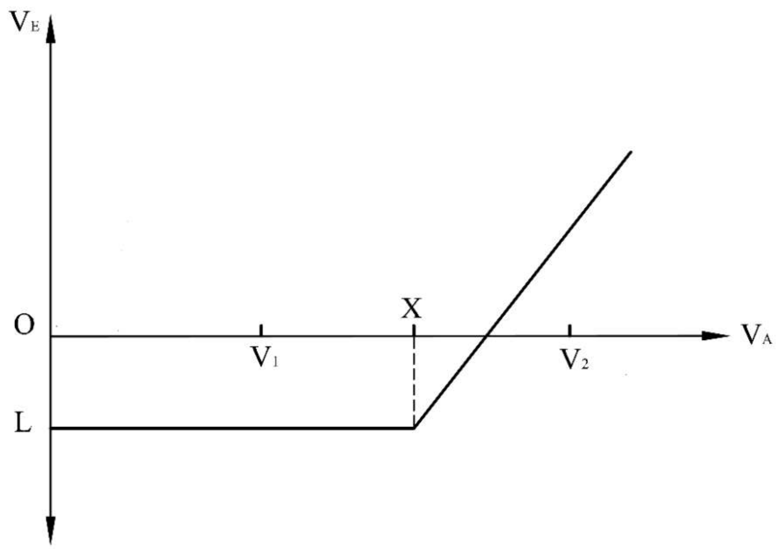
The reason is that shareholders are residual claimants on the firm's assets after all other obligations have been met. According to Merton's theory, it is just as the shareholders sold the corporation to their creditors, they have the right, but not the obligation to pay off the creditors. The relation between equity value V_E (y-axis) and firm's asset value V_A (x-axis) is shown in Figure 3.1. At the maturity of the option, if the value of the firm's assets (take the point V_2 as example) is greater than the book value of liabilities *X*, the shareholders exercise their option on the assets, and the firm continues to exist. Otherwise, if the firm's asset value (take the point V_1 as example) is lower than the book value of liability *X* at maturity, the shareholders will choose not to exercise the option right and the value of equity is zero, which means the firm will default.

Thus, the market value and volatility of the firm's underlying assets implied by the equity's market value are important to determine to what extent a firm will go bankruptcy. However, the market value and volatility of the firm's assets are usually cannot obtained directly. In

[34] Jarrow and Turnbull (1995), Duffie and Singleton (1999)

particular, Merton solves backward from the option price and option price volatility for the implied asset value and asset volatility.

Figure 3.1 Equity as a European call option on the firm



Firstly, recall that the assumption of Black-Scholes (BS) model is that the market value of a firm's underlying assets follows the following Geometric Brownian Motion (GBM):

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{3.5}$$

where V_A and dV_A are the firm's asset value and its change, μ and σ_A are respectively an instantaneous drift rate and the instantaneous volatility of firm's asset value, and dW is a standard Weiner process.

Besides, the BS model also assumes that the capital structure has only a single class of debt and a single class of equity.

Then, under these assumption and following Merton's theory, denote *X* as the book value of liability that maturing at *T*, the market value of firm's equity V_E can be seen as a European call option on firm's underlying assets V_A with has maturity equal to *T*, which is given by the BS formula for call options:

$$V_E = V_A N\left(d_1\right) - Xe^{-rT} N\left(d_2\right) \tag{3.6}$$

where,

$$d_1 = \frac{ln\left(V_A/X\right)+\left(r+\frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}},\ d_2 = d_1 - \sigma_A\sqrt{T} = \frac{ln\left(V_A/X\right)+\left(r-\frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}},$$

N is the cumulative density function of the standard normal distribution, r is the risk-free rate, and Xe^{-rT} is the present value of the promised debt payment.

Next, to solve the two unknown parameters V_A and σ_A in equation (3.6) which implies that the equity value can be represented as a function of the asset value, Merton applies Ito's Lemma[35] to determine an instantaneous standard deviation of equity that can be otherwise estimated from the historical share prices.

Follows from Ito's lemma, the relation between equity value volatility σ_E and the asset value volatility σ_A is as follows:

$$\sigma_E = \frac{V_A}{V_E}\Delta\sigma_A = \frac{V_A}{V_E}\cdot\frac{\partial V_E}{\partial V_A}\cdot\sigma_A = \frac{V_A}{V_E}\cdot N\left(d_1\right)\cdot\sigma_A \tag{3.7}$$

where the hedge ratio Δ equals to $\frac{\partial V_E}{\partial V_A}$ which is the partial derivative of the equity value with respect to the asset value, and from BS formula of equation (3.6), it can be shown that the hedge ratio $\frac{\partial V_E}{\partial V_A} = N\left(d_1\right)$.

Combines equation (3.6) and equation (3.7), asset value and its volatility are calculated.

The default probability DP_t is the probability that the firm's assets value is less than the book value of the firm's liabilities, based on which, Merton derives the firm's probability of default (the details of derivation process are shown in Appendix E) in terms of the cumulative normal distribution:

$$DP_t = N\left(-\frac{ln\left(\frac{V_{A,t}}{X_t}\right)+\left(\mu-\frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right) \tag{3.8}$$

[35] For a rigorous discussion of Ito's Lemma, see McKean (1969) and for references to its application in portfolio theory, see Merton (1973b)

Merton's distance-to-default (DD) is the number of standard deviations that the firm is away from default, which means that the higher the DD, the farther the firm is away from default (the lower probability of default), on the contrary, the lower the DD, the higher probability of the firm bankrupt.

$$DD = \frac{ln\left(V_{A,t} / X_t\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \tag{3.9}$$

$$DP = N\left(-DD\right) \tag{3.10}$$

The major advantage of BSM option-pricing model in predicting default risk is that "they provide guidance about the theoretical determinants of bankruptcy risk and they supply the necessary structure to extract bankruptcy-related information" Hillegeist et al. (2004).

Unlike the accounting-based models that are constructed by comparing the characteristics of bankrupt and no bankrupt firms, using a statistical technique to derive the variables that best discriminate between the two groups of firms which are not grounded in theory, and distinguish firms of bankruptcy or no bankruptcy heavily dependent on the prior specification of firms. The equity of a firm can be viewed as a call option on the firm's assets leads to a measure of default risk that is derived from theory and is economically justifiable.

Furthermore, compared with the conventional accounting-based models, it is more forward-looking, dynamic and easier for using because it is calculated based on the market prices which reflect future expected cash flows (the accounting-based models, on the contrary, reflect the past performance of the firms), and contain the information comes from financial statements plus other information not included in the financial statements.

Among plenty researches that implement BSM model, one of the most popular and commonly used is KMV model, which will present in the next section.

3.2.2.2 KMV model

KMV model was first introduced by Oldrich Vasicek and Stephen Kealhofer Vasicek (1984) also as an extension of BSM model. In 1989, Kealhofer, McQuown, and Vasicek set up the KMV Company which is named by the founder's names and later in 2002 was bought by the company Moody´s. Then KMV is set to the successful practical model that estimated the default risk of firms.

Though BSM option-pricing model is the genesis for understanding the link between the market value of the firm's assets and its equity, and is widely understood and provides a useful framework to estimate firm's DP. KMV model assumes "the firm's equity is a perpetual option with the default point acting as the absorbing barrier for the firm's asset value" Crosbie and Bohn (2003), the firm is assumed to default when the asset value hits the default point. Unlike BSM model, allows only two types of liabilities, a single class of debt and a single class of equity, KMV model takes multiple classes including short-term liabilities, long-term liabilities, convertible debt, preferred equity, and common equity of liabilities into consideration.

There are three main steps to determine default probability of KMV model, we will present precisely the differences from BSM model in each step.

- *Step 1 Estimate firm's asset value and its volatility*

The BSM model applies the method called "simultaneous equations method" to solve firm's asset value and volatility, that is solving the combination of tow equations (3.6) and (3.7) to obtain two unknown parameters. However, the model which presents the links between asset value and volatility given by equation (3.7) holds instantaneously. (Crosbie and Bohn, 2003) emphasize that "*In practice the market leverage moves around far too much for equation (3.7) to provide reasonable results. Worse yet, the model biases the probabilities in precisely the wrong direction*". For instance, in equation (3.7), if the market leverage (V_A / V_E) decreases then the asset volatility σ_E will tend to be overestimated and thus the default probability will be overstated as the firm's credit risk improves. On the conversely, if the market leverage increases the asset volatility σ_E will be underestimated and the default probability will be understated.

Instead of using instantaneous relationship in equation (3.7) and "simultaneous equations method" to solve the two unknown parameters of the Merton' option pricing formula (3.6), KMV model Crosbie and Bohn (2003) resolve the problem by using a complex iterative procedure to find value of firm's asset and volatility. The procedure uses an initial guess of firm's asset volatility σ_A and then solve the equation (3.6) to determine a set of the firm's asset value V_A and thus obtain the asset returns. Then the volatility of the resulting returns is used for the next iteration to determine a new set of V_A and therefore a new series of asset returns. The procedure continues like this until the results converge.

- *Step 2 Calculate the default point and distance-to-default*

To calculate the DD of Moody's KMV, an important concept is default point. A firm default if the market value of assets falls below a certain value which is called the default point, and it is generally accepted that the firm reaches the default point when the value of asset less than its total liabilities. However, Crosbie and Bohn (2003) find in general this is not the case, the default commonly occurs when the market value of firm's asset locates between the total liabilities or total debt and the short-term (current) liabilities (debt). In KMV model, the default point is calculated as short-term debts (STD) plus one-half of long-term debts (LTD).

$$\text{Default Point} = STD + \frac{1}{2} LTD \tag{3.11}$$

Moody's KMV argues that in fact, the distribution of the DD is difficult to measure, so the assumption of normal or lognormal distribution such as BSM model is not appropriate to use in practice. KMV model proposes the DD which "*compares the market net worth to the size of a one standard deviation move in the asset value*":

$$DD_{KMV} = \frac{V_A - \text{Default Point}}{V_A \sigma_A} \tag{3.12}$$

where V_A is the market value of firm's assets and σ_A is asset volatility. The numerator in the formula is the firm's market net worth which equals to the value of assets minus the default point, a firm will default when its market net worth reaches zero.

- *Step 3 Calculate the Expected Default Frequency based on the empirical distribution of the DD*

BSM model calculates the DP (default probability) as the normal distribution of negative DD, whereas, Crosbie and Bohn (2003) point out that in practice the normal distribution is a very poor choice to define the probability of default, because Moody's-KMV observe that defaulted firms have a leptokurtic distribution and the normal distribution underlying the BSM model leads to underestimation of the true value of firm's DP.

To avoid this effect of using the normal distribution, after calculating the distance-to-default, the KMV use their own large default database[36] which collected over 20 years, to derive an empirical distribution relating the DD to the DP. The empirical distribution obtained from the KMV's proprietary database has much wider tails than the normal distribution.

This DP is well known as Expected Default Frequency (EDF), which is the market-based credit measure developed by Moody's KMV. The EDF is nothing but the probability that a

[36] Their database includes over 250,000 company-years of data and over 4,700 incidents of default or bankruptcy.

given firm will default within 1 year according to the KMV methodology. The formula of EDF is similar as BSM's DP of equation (3.10), the normal distribution N is replaced by the empirical distribution of KMV which we can denote $\tilde{N}_{KMV}$:

$$EDF = \tilde{N}_{KMV}\left(DD_{KMV}\right) \tag{3.13}$$

Moody's KMV has also a software product which is called 'Credit Monitor' to analyze the EDF credit measures, one can calculate the EDF values for one to five years through Credit Monitor.

Many researchers go for KMV's claim and argue that it is inconsistent to derive a formula for calculating DP based on an underlying normal distribution and then depart from KMV's empirical distribution in the final calculation of the DP. A large number of world financial institutions are subscribers of the KMV model.

From a purely theoretical point of view, the differences between KMV and Merton's models are not dramatic. The KMV model, however, relies on an extensive empirical testing and it is implemented using a very large proprietary database.

3.2.3 Hazard model

Shumway (2001) find that many accounting ratios used in previous models (Altman (1968 and Zmijewski (1984) for estimating default probability are not statistically significant, instead, the market size, past stock returns and idiosyncratic standard deviation of stock returns are all strongly related to the firm's bankruptcy. The author argues that the static models do not consider the time-changing characteristics of firms and propose a discrete-time hazard model to predict bankruptcy by using both accounting ratios and market variables, which is a better predictor of bankruptcy than alternative models.

The concept of Shumway's hazard model comes from the survival model that estimates firm's hazard rate according to the sample's survival condition. In other words, "a typical discrete-time hazard at time t can be interpreted as a conditional probability of default at time *t*, given that the default did not happen prior to time *t* Outecheva (2007)". There are two main functions to understand the hazard model: the survivor function

$$S\left(t,x;\theta\right)=1-\sum_{j<t} f\left(j,x;\theta\right) \tag{3.14}$$

and the hazard function

$$\phi(t,x;\theta)=\frac{f(t,x;\theta)}{S(t,x;\theta)} \tag{3.15}$$

where, $f(t,x;\theta)$ is the probability function of default, and θ is the vector of parameters of f, x is a vector of explanatory variables for predicting default. The survivor function (3.14) gives the probability of surviving up to time t, and the hazard function (3.15) gives the probability of failure at t conditional on surviving to t

To estimate hazard function, many of which are difficult to estimate because of their nonlinear likelihood functions and time-varying covariates. Shumway shows that the discrete-time hazard model has the same likelihood function as logit model:

$$L=\prod_{i=1}^{n}\phi(t_i,x_i;\theta)^{y_i}S(t_i,x_i;\theta) \tag{3.16}$$

y_i is a dummy variable which equals one if firm i default at t_i or equal to zero if otherwise. So it is possible to estimate a hazard model with a logit program by "*adjusting the sample size assumed by the logit program to account for the lack of independence between firm-year observations*"[37].

Chava and Jarrow (2004) prove that the prediction ability for the bankruptcy of Shumway's hazard model is superior to accounting-based models (Altman (1968) and Zmijewski (1984)), in addition, they find that "*accounting variables add little predictive power when market variables are already included in the bankruptcy model*". Campbell et al. (2008) also develop a dynamic hazard model to estimate the default probabilities and study the determinants of corporate bankruptcy and the pricing of distressed stocks. They declare that their best model includes additional variables and has greater explanatory power than the existing models estimated by Shumway (2001) and Chava and Jarrow (2004).

3.2.4 Comparing Accounting-based models and market-based models

In summary, the market-based models overcome the main shortcomings we mentioned at the beginning of the section 3.2.2 about accounting-based models:

[37] In the static logit model, the number of firm-years is used in calculating the Wald statistics. However, this is not correct for the dynamic logit model because in the dynamic logit model, unlike the static logit model, firm-year observations are not independent of each other. For the dynamic logit model, it is the number of firms rather than the number of firm-years that should be used.

- The most importantly, market-based models employ BS option-pricing theory provide the theoretical basis for predicting firm's default risk or distress risk. While the accounting-based models are not grounded on the economic theory.

- Dissimilar accounting-based models that use information derived from financial statements which reflect the past performance of the firms, market-based model such as BSM model, depend on the market prices which reflect investors' expectations about the firm's future performance, thus the market-based models are better for calculating the probability of default in the future. Furthermore, the market prices contain the information in financial statements and other information which is not included in the financial statement.

- Market-based variables provide the direct estimation of volatility, which is a powerful predictor of firm's default risk and is not contained in the accounting-based model.

Hillegeist et al. (2004) compare the performance of two accounting-based models (Altman's Z-score and Ohlson's O-score) and the market-based model (BSM option-pricing model), and their results demonstrate that BSM model provides significantly more information of bankruptcy probability than both accounting-based models. They recommend researchers to apply BSM model instead of Z-score and O-score proceeding the research.

Despite the popularity and the advantages of market-based models to predict firm's default risk, there are still some critics left for market-based models, such as the models based on the underlying option-pricing theory require the assumption of normality of stock returns and the models do not distinguish between different types of debt and assume that the firms only have a single zero coupon loan[38]. Many researchers give the evidence that accounting-based models are still indispensable in predicting distress risk.

Using a hazard model with a longer time period, Beaver et al. (2005) finds that the ability of accounting ratios to predict bankruptcy remains. Their findings indicate that the market variables complement accounting variables and that the use of market variables causes only a slight reduction of predictive power of the accounting variables in certain sub-periods.

Agarwal and Taffler (2008) find out that there is little difference between market-based models and Altman's model in predicting firms' distress risk in the UK, and the accounting-based model even produces significant economic benefit over the market-based models. In the paper of Reisz and Perlich (2007), they estimate the default probability for

[38] Allen and Saunders (2002)

5784 industrial firms and conclude that Altman's Z-score model better predict firm's bankruptcy over a one-year horizon. Moreover, Campbell et al. (2008) find that market-based models have little forecasting power after controlling for other variables.

To conclude, when comparing the two mainstream distress risk prediction models: accounting-based models and market–based models, we can say that both imply advantages and disadvantages.

3.3 Financial distress risk and equity returns

In the asset pricing area, as we all know that the market risk cannot explain all the variation of average stock returns, researchers have been committed to exploit the anomalies which have additional explanatory power. One of the anomalies that researchers are interested in is the firm's distress risk, the cross-sectional relation between default risk and stock returns, the so-called default risk premium, has been a subject of intense debate in the literature. numerous studies apply the models for measuring distress risk and try to find the relation between expected stock returns and firm's distress risk.

Since a number of empirical studies investigating the relationship between financial distress risk and equity returns find that the distress risk is related to firm's B/M ratio, especially after FF3F model achieves huge empirical success, considerable researchers regard financial distress risk as a factor and examine whether distress risk factor can be explained (proxy) by FF factors.

3.3.1 Literature reviews on developed markets

3.3.1.1 Distress risk and expected stock returns

In order to find out the relation between distress risk and equity returns, it is important to have a correct proxy for distress risk, and "*the risk of bankruptcy appears to be one natural measure of firm distress*" Dichev (1998), thus the diverse models of measuring firm's default probability provide the rational proxies for distress risk. The empirical studies on the distress premium mainly apply either the traditional accounting-based models such as Altman's Z-score and Ohlson's O-score[39] or the market-based models such as Merton's

[39] Dichev (1998), Griffin and Lemmon (2002) and Ferguson and Shockley (2003), etc.

option-pricing model and Moody's KMV model [40] to estimate distress risk (default risk/probability). A few researchers also apply the dynamic reduced-form model such as Shumway's hazard model as a proxy for distress risk.

Dichev (1998) is the first who carries out researches on the relationship between default risk and stock returns, by applying Altman's Z-score and Ohlson's O-score as proxies for default risk. Dichev examines whether bankruptcy risk is a systematic risk and the relation of distress risk factor to size and B/M effects on U.S. market during the period 1981 to 1995. His findings reveal that the risk of bankruptcy is not a systematic risk and there is a negative relationship between bankruptcy risk and stock returns, firms with higher default risk are rewarded by lower average returns instead of higher returns, which is inconsistent with the risk-based explanation for distress, this puzzling relation between distress risk and stock returns is often called the "distress anomaly. Furthermore, inconsistent with some studies[41] which suggest that the size and B/M effects may the proxies of the distress risk factor, his results demonstrate that the relationship between bankruptcy risk and B/M equity ratio is not monotonic, thus "*a return premium related to bankruptcy risk cannot fully explain the B/M effect*", and there is no size effect during his research period.

Dichev's conclusion is confirmed by Griffin and Lemmon (2002) who examines the relationship between B/M equity, distress risk and stock returns using Ohlson's O-score as a proxy for firm's distress risk. Similarly, they find that firms with high B/M equity ratio earn significantly lower returns as a premium for distress risk than those of low B/M firms and they come to a conclusion that the B/M effect must be due to mispricing.

Numerous researches following obtain the negative relationship as Dichev, Campbell et al. (2008) and Campbell et al. (2011) implement a dynamic hazard model for predicting firm's distress risk by combining both accounting information and market-based measures over the period 1981 to 2003, and they document that the default probability is significantly negatively related to stock returns, which becomes even more stronger after controlling for size. They give some possible explanation for the distress anomaly: the stocks of firms with higher distress risk are overestimated by investors, and "*distressed stocks have characteristics that appeal to certain investors, such as increased opportunities to extract private benefits of control or positive skewness of returns*". Likewise, George and Hwang (2010) also report a negative relation between stock returns and default risk measured by the O-score.

However, there are a few researchers find the positive relationship between distress risk and stock returns, such as Vassalou and Xing (2004) which is the first study that examines

[40] Vassalou and Xing (2004), Garlappi and Yan (2011) Gharghori et al. (2009), etc.
[41] Fama and French (1992), K. C. Chan et al. (1985), Chan and Chen (1991), etc.

default risk in the context of the Fama-French model by extracting default risk estimated from Merton's option pricing model. Inconsistent with Dichev, they point out that the default risk is a systematic risk, and the default risk is closely related to the firm size and B/M equity ratio, there exist size and B/M effects but only within the highest default risk portfolios. Moreover, contrary to the previous empirical studies, firms with higher default risk earn higher returns than low default risk firms, however, this finding only lies in the small size and high B/M portfolios. They attribute these conflicting results to the measurement for estimating default risk.

Chava and Purnanandam (2010) also document a positive and stable cross-sectional relation between default risk and expected stock returns throughout their research period. They argue that the negative relation between distress risk and expected returns is due to "*the use of noisy ex-post realized return by the prior studies to estimate the ex-ante expected return*". Then the implied cost of capital (ICC) is applied to estimate the expected stock returns, and the two measures to predict firms' default risk are EDF of KMV model and Shumway's hazard model.

Recently, apart from using accounting-based models or market-based models as proxy of distress risk, Friewald et al. (2014) examine the relation between expected stock returns and credit risk premium estimated from credit default swaps (CDS) spreads, as they claim that "*sorting firms into portfolios using only physical or risk-neutral default probabilities may not be sufficiently informative about expected stock returns*". Their results indicate a positive relationship between the expected excess stock returns and default probabilities, the stock returns increase with credit risk premium. Their findings are conflictive with Avramov et al. (2007) who use credit ratings to measure financial distress, show that stock returns significantly increase with S&P senior debt credit ratings, which implies a negative relationship between returns and default risk. show that most of the negative return for high default risk stocks is concentrated around rating downgrades.

The literature generally has the conclusions that there exist negative or positive or no relationship between stock returns and distress risk. Nonetheless Garlappi et al. (2008) and Garlappi and Yan (2011) document particularly a hump-shaped relationship using market-based default probability estimates from Moody's KMV model. The results demonstrate that the higher distress risk not always associated with higher expected stock returns. Furthermore, they emphasize the important role of the 'shareholder advantage' in determining the equity returns, the higher shareholder advantage the lower expected equity returns as the default probability increases, and lower shareholder advantage which implies a higher expected equity returns is positively related to default risk. As they expressed "*the trade-off between the risk of default to equity and the likelihood of bargaining gains in* *renegotiation results in a hump-shaped relationship between expected returns and default probability*".

Out of U.S. market, Gharghori et al. (2009) test the relationship between default risk and equity returns in Australia using option-based models as proxy for distress risk. Their results show that there is a negative relationship between default probability and stock returns, what's more, they also suggest that the negative relationship is not because of a leverage, volatility or momentum effect.

Aretz et al. (2014) provide the evidence on the cross-sectional relation between default risk and stock returns for non-U.S. firms in 14 developed markets using the approach of Campbell et al. (2008, 2011). Their results demonstrate a statistically significant positive default risk premium in the 14 international markets, the firms with higher default risk outperform those with lower default risk. In addition, their results also indicate that "*the magnitude of the default risk premium is contingent upon several firm characteristics*".

3.3.1.2 Distress risk factor

Vassalou and Xing (2004) point out that their default probability (DP) estimated using Merton's model is not the real DP, instead, the DP calculated based on the empirical distribution by Moody's KMV model is the actual DP. Thus they call their measure of DP default likelihood indicator (DLI). In order to construct the distress risk factor, they proceed following steps: first state the aggregate default likelihood measure *P(D)* which is the simple average of the DLI of all firms; then define the aggregate survival rate *SV* equals to 1- *P(D)*; finally, the distress risk factor is defined as the change of *SV*:

$$\Delta\left(SV\right)=SV_t-SV_{t-1} \tag{3.17}$$

Equation (3.17) represents the change in aggregate survival rate $\Delta\left(SV\right)$ at time *t*. The authors also examine the correlation between $\Delta\left(SV\right)$ and several commonly used default spreads[42], the low correlations indicate that the information captured by their $\Delta\left(SV\right)$ is different from that captured by those default spreads.

[42] Default return spread, which is defined as the return difference between Moody's BAA rating bonds and AAA rating bonds. Default yield spread, which is defined as the yield difference between Moody's BAA bonds and AAA bonds. The change in default spread from Hahn and Lee (2001), which is defined as the change of the difference in the yields between Moody's BAA bonds and 100-year government bonds.

Another distress risk factor proposed by Gharghori et al. (2007) is a mimicking portfolio which measures the difference in returns between high default risk firms and low default risk firms. They also apply Merton's option-pricing model to calculate firms' default probability, and similar as Vassalou and Xing, they augment FF3F model with their distress risk factor to test whether FF factors SMB and HML can proxy for distress risk. We will follow the later method to construct our distress risk factor on CNAS stock market.

3.3.2 Empirical studies of distress risk on Chinese stock market

To the best of our knowledge, the research on Chinese market mainly focuses on testing the predictive accuracy of commonly used models in estimating distress risk using data of Chinese listed firms and measuring default risk of Chinese companies without considering the relationship between default risk and stock returns.

Wang and Campbell (2010b) investigate the prediction accuracy of Altman's Z-score in estimating Chinese firms' failure using data from 2000 to 2008, and point out that Z-score has high accuracy in predicting firms' failure in China. In the same year, they Wang and Campbell (2010a) publish an article that examines the predictive ability of another leading accounting-based model (Ohlson's O-score) for Chinese listed firms, in which the prediction accuracy rate is testified above 95% in general. Likewise, Ni et al. (2014) show that accounting-based models (Altman's Z-score and Ohlson's O-score) perform reasonably well in determining business failures of Chinese firms.

Huang et al. (2013) use Altman's Z-score and Ohlson's O-score to measure the financial distress risk of all nonfinancial firms of A-share stock market for the period 1997 to 2008, trying to test whether there exist value or size effect. Their results show that firms with small size have higher distress probability than firms with big size, while there is no significant difference in distress probability for firms with different B/M equity ratio. In addition, when the distress risk factor is added into their conditional regressions, the size factor SMB of FF3F model lose more than half of explanatory power, however, "*the proxy for distress risk itself does not show incremental explanatory power when competing with the three Fama-French factors*". Overall, they conclude that the size factor is better than distress risk factor in explaining variations of expected stock returns on Chinese stock market.

Apart from the literature that tests the accounting-based models in China, there are researchers examine the practicability of the market-based model (Merton's model and Moody's KMV model) in predicting distress risk of Chinese listed firms. Such as Lu et al. (2006), Zhou and YANG (2007), Xiaohong Chen et al. (2010) and Chen and Chu (2014), who apply KMV model to estimate distress risk; Liang (2012) and Law and Roache (2015), who calculate firms' distress risk using models based on Merton's theory.

Particularly worth mentioning, most of the literature using KMV model to measure distress risk of Chinese firms have discussed that it is not appropriate to apply KMV's EDF in calculating firms' default probability, since KMV model use an empirical distribution derived based on the database of U.S. market. At present, as stated by Xiaohong Chen et al. (2010), "*there is no similar database in Chinese credit market, which means no EDF statistics is available*", so researchers use DD of KMV model instead of the DP as the measure of distress risk in China.

Xiaohong Chen et al. (2010) measure credit risk of listed firms of Small Medium Enterprise Board (SME) in China using KMV's DD and evidence indicates the high credit risk of listed firms in SME. Moreover, they find firms' size has a significant impact on credit risk, the small size firms tend to have higher default probability than medium and large size firms. Chen and Chu (2014) implement an empirical research for the default risk of Chinese real estate firms during the period 2007 to 2012. They implement KMV model as proxy for distress risk and contrary to Xiaohong Chen et al. (2010) that they find big size firms face higher default risk than small size firms.

Liang (2012) tests the predictive ability of DLI (Vassalou and Xing, 2004) by using data of Chinese listed firms during 2000 to 2010, and the results reveal that the DLI based on Merton's model is a significant model for predicting distress risk on Chinese stock market. What's more, the author augments the original Merton-KMV model with financial ratios (profitability, leverage, and liquidity) and compare the augmented model with Merton-KMV model and accounting-based model. The evidence shows that the original Merton-KMV model can be improved by an augmented model and the accounting-based model is the weakest one in measuring default risk on Chinese stock market.

More recently, Law and Roache (2015) assess Chinese firms' distress risk using a variant of Merton's model and link the default risk with firm-specific and economic variables to test whether they have an influence on firms' default probabilities. Furthermore, the authors compare the result with that obtained from a model using borrowing cost as a measurement of default probability. They conclude that the distress risk measured by the market-based model is affected by firms' fundamentals, and that market-based model better estimates the stand-alone 1-year probability of default for individual firms in China.

Several researchers exploit distress predictive models themselves depending on the data of Chinese firms, such as Geng et al. (2015), who build financial distress warning model based on 32 financial indicators of 107 Chinese firms which are 'special treatment' (ST)[43]. And some other researchers such as Bhattacharjee and Han (2014) and Liu and Wang (2016) trying to find the impact of some macroeconomic, firm-specific variables and the cutoff point on the financial distress risk of Chinese listed firms.

Lin and Chen (2008) is one of the few studies that investigate the relationship between distress risk and expected stock returns on Chinese stock market. They examine whether default risk is a systematic risk in China and related to expected stock returns using data of Chinese stock market from 2000 to 2006 by applying Vassalou and Xing's DLI to calculate firms' default probabilities. The empirical evidence demonstrates that the default risk is not a systematic risk and there is no significant relationship between the expected stock returns and the implied default risk, even controlling for size and B/M equity ratio.

Our research does not aim to find a better distress predictive model or to examine the predictive accuracy of existing models on Chinese stock market. Since the lack of literatures that discuss the relation between distress risk and expected stock returns in China, we devote ourselves to explore the relationship based on the framework of Fama-French Three-Factor Model and examine whether FF factors can proxy for distress risk calculated through the most popular and commonly used models which have been proved able to predict distress risk on Chinese stock market, in addition, whether an augmented four-factor model with distress risk factor can explain expected excess stock returns better on CNAS stock market.

3.4 Construct distress risk factor and portfolios on Chinese stock market

3.4.1 Data

All the data needed in this study during the period July 2005 to May 2015 (119 months) is collected from Bloomberg, and in research of both methods, we exclude the financial firms, the capital structure of which is distinguished from that of common ones, and the firms with negative B/P ratios also removed from the sample as Chapter 1. Since our research focuses on the healthy firms, the firms which labeled as 'ST' and 'PT' are also out of our

[43] China Securities Regulatory Commission carries out a 'Special Treatment' (ST) warning mechanism to indicate abnormalities in a listed companies' financial status Geng et al. (2015), firms will labeled as ST if they have negative profits for two consecutive years and the equity of shareholders is less than the registered capital, even may be delisted from the stock market if their performance will not improve within next three years.

consideration. We exclude the firm if one has incomplete data at certain months. To proceed our research and to perform the comparison, first of all, we calculate the default probability using accounting-based model (Ohlson's O-score) and market-based model (Merton's option-pricing theory) separately. These default probabilities are then used as a basic criterion for the distinction of firms' distress risk.

3.4.1.1 Calculate default probability by O-score and DLI

- *O-score as proxy of distress risk*

Due to the limitations of Altman's Z-score, such as the strict statistical assumption of MDA, especially, the Z-score is rather a value measuring of financial strength with little intuitive interpretation. We choose Ohlson's O-score which measures the probability of financial distress.

To be included in our sample, a firm must have two-year ahead data of net profitability for the purpose to calculate the O-score and at least 12-month data of returns. We calculate the O-score of stocks formula (3.4) with our database at the end of each December during the research period July 2005 to May 2015. Particularly, consistent with Dichev (1998), we do not adjust for the 'GNP price-level index' of the first 'SIZE' variable in formula (3.4) because the tests in this study employ monthly data, within which the index is fixed. Thus the 'SIZE' in the formula (3.4) equals to log (total assets).

- *DLI as proxy of distress risk*

Following Vassalou and Xing (2004), we compute DLI (equation (3.8)) by applying the methodology developed by Black and Scholes (1973) and extended by Merton (1974) to estimate default probabilities of the individual firms on CNAS stock market. There are two main reasons why we use Merton's theory instead of using EDF of KMV model to calculate distress risk in China: Firstly, as many researches emphasize that the empirical distribution of KMV is deduced based on database of U.S. market, while there is not such a distribution in China, it is not correct to apply EDF to estimate distress risk on Chinese stock market; secondly, after empirical analysis of defaults, KMV has found that firms most frequently reach the default point when the firm's value approximately equals to short-term (current) liabilities plus 50 percent of long-term liabilities. However, whether the default point is the same on the Chinese stock market is still a question, it is not a responsible way to calculate KMV's DD based on their default point.

To calculate DLI, we need to solve Black-Scholes formula (3.8) and obtain two unknown variables V_A (asset value) and σ_A (asset volatility), with input value of equity V_E (market capitalization, equals to share price times the shares outstanding), strike price X which is the book value of liability, risk-free interest rate r and maturity T. We follow the approach of Moody's KMV Crosbie and Bohn (2003) and Vassalou and Xing (2004), applying a more complex iterative procedure to solve for the asset volatility σ_A and value of firm's asset V_A:

- Step 1, at the end of each year, we calculate the daily returns of firms' equity from the past 12 months to obtain the volatility of equity σ_E, which is as the initial estimate of σ_A.
- Step 2, then we use daily V_E and this initial estimation σ_A to solve the Black-Scholes formula on each trading day for the past year to get daily estimates V_A.
- Step 3, we next take the standard deviation of those V_As as the new estimate of σ_A, which is used for the following iteration procedure.

Step 2 and 3 above are repeated until the value of σ_A from two consecutive iterations converge with the tolerance level 0.001. Once we obtain the converged value of σ_A, we use it to find out our final estimation V_A. Then we calculate DD using equation (3.9) at each year-end over our sample period, DLI is then denoted by the cumulative density function of the standard normal distribution of subtractive DD (equation (3.10)).

Furthermore, we always calculate default probability with a one-year horizon. The risk-free rate also needs to be a yearly rate, here we use one-year fixed deposit rate which is officially determined by the People's Bank of China. There are at least three reasons why the time to maturity is set to one year: first, choosing one year permits comparability with prior research such as Griffin and Lemmon (2002), Vassalou and Xing (2004) and Lin and Chen (2008); second, a maturity of greater than one year is difficult to justify as there are too many factors (firm specific and economy-wide) that may affect a firm's DP over time; third, one-year maturity represents a reasonable balance between the weight placed on market leverage, asset volatility, and asset growth rate in the construction of the DPs Gharghori et al. (2006).

3.4.1.2 Summary description of O-score and DLI

Our research period is from 2005 to 2014, mainly because the number of firms that have data of O-score is rare before 2005. The annual available number of firms for which O-score and DLI could be calculated are displayed in Table 3.2, it is obvious that there are few firms which have available data of O-score before 2005 (0 for the year 2002 and 2003, 7 for the year 2004).

Table 3.2 Annual available number of firms whose O-score and DLI can be calculated

This table presents the annual number of firms which have available O-score and DLI from the year 2002 to the year 2014, "-" indicates the data which is not available.

Year	O-score	DLI	Year	O-score	DLI
2002	0	**-**	**2009**	1178	1370
2003	0	**-**	**2010**	1205	1389
2004	7	822	**2011**	1226	1676
2005	938	1109	**2012**	1252	1997
2006	1013	1146	**2013**	1285	2193
2007	1128	1160	**2014**	1356	2259
2008	1151	1255			

The annual aggregate O-score and aggregate DLI from 2005 to 2014 are presented in Figure 3.2 and Figure 3.3 respectively, from which we could see that the tendency of both figures is similar. Both the aggregate O-score and aggregate DLI increase dramatically from 2008 to 2009, the period which is well known as the recession period because of the worldwide financial crisis, while the aggregate default probability decreases sharply (2009-2010) during the period of economic recovery.

Figure 3.2 Annual aggregate O-score (2005-2014)

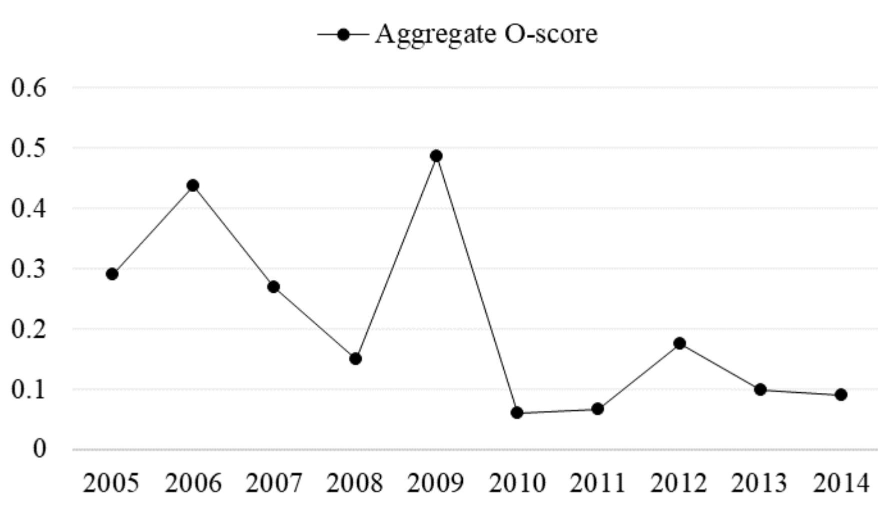
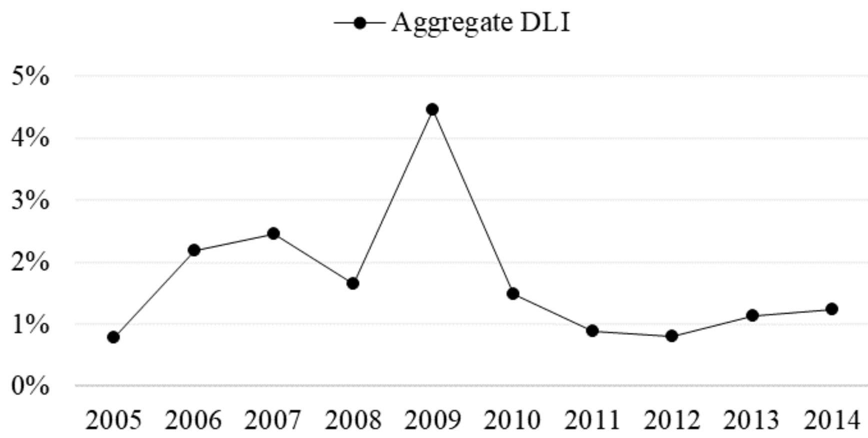


Figure 3.3 Annual aggregate DLI (2005-2014)



3.4.2 Construction of distress factor and portfolios on Chinese market

3.4.2.1 Portfolios construction using O-score and DLI as proxy of distress risk

In Chapter 1, we sort stocks both into 6 (2x3) and 25(5x5) Size-B/P portfolios and we find that the different sorts of portfolios do not affect the empirical results. In this chapter, we construct 18 (2x3x3) Size-B/P-O-score (SBPO) portfolios as follows:

Similarly, like FF six portfolios, we sort stocks into two size portfolios (Small and Big) and three B/P portfolios (Low, Medium and High). The size breakpoint for year *t* is the median CNAS market capitalization at the end of June of year *t*. B/P ratio for June of year *t* is the book value of equity for the last fiscal year end in *t-1* divided by the price for December of *t-1*, the breakpoints are the 30th and 70th CNAS percentiles. At the end of each year *t-1*, O-score for year *t* is calculated using Ohlson's formula (3.4) for each stock, then stocks are sorted into 3 distress risk (DR) groups (O1, O2 and O3, which represent the low, medium and high O-score groups, separately) according to their O-score with the breakpoint 30th and 70th percentiles.

The 18 portfolios which are constructed at the end of each June of year *t*, are the intersection of two size portfolios, three B/P portfolios, and three O-score portfolios, we denote the portfolio which has small size, low B/P ratio and low DR as SL1, the portfolio which has small size, low B/P ratio and medium DR as SL2, and so on the 18 portfolios are denoted by SL1, SL2, SL3, SM1, SM2, SM3, SH1, SH2, SH3, BL1, BL2, BL3, BM1, BM2, BM3, BH1, BH2, and BH3. Portfolios are reconstructed in June of each year. The distress risk factor DRF is the difference between average returns of high O-score portfolios and low O-score portfolios.

Following exactly the same process, we construct 18 Size-B/P-DLI (SBPD) portfolios with two size portfolios, three B/P portfolios and three DLI portfolios (D1, D2, D3 are the low DLI portfolio, medium DLI portfolio, and high DLI portfolio, respectively). The three DLI portfolios are constructed in the same way that three O-score portfolios are done above, except that the basis criterion for distinguishing firms' distress risk is DLI instead of O-score.

3.4.2.2 Construction of distress risk factor

The proxies of distress risk we use are the DP calculated by O-score and DLI stated in the previous section. At the end of each June of year *t*, we sort stocks according to their O-score (or DLI) of the end of year *t-1* into three groups, denoted as O1, O2 and O3 (or DLI1, DLI2, DLI3) from low to high default probabilities. The breakpoints are 30% and 70% percentiles of the O-score (or DLI) of the sample firms. The portfolios remain unchangeable from July of year *t* to June of year *t+1*, and portfolios are reformed at the end of June of year *t+1*, and so forth for the whole sample period. The mimicking portfolio DRF is the distress risk factor, which measures the return difference between the high-DP portfolio (O3 or DLI3) and the low-DP portfolio.

3.5 Distress risk, size and B/P ratio of Chinese stock market

Numerous studies suggest that a firm distress risk factor could be behind the size and the value effects. For instance, Griffin and Lemmon (2002) and Vassalou and Xing (2004) both show that the B/M and size effects are concentrated in high default risk firms, thus leding to the conjecture that the value and size effects are closely related to distress risk.

We aim to investigate whether there exist size and value effects on CNAS stock market related to the distress risk in this section. In order to compare whether different methods of measuring distress risk have different impact to our empirical results, we apply both of the leading models, accounting-based model of Ohlson's O-score and market-based model according to Merton's option-pricing theory, to estimate the distress risk of Chinese listed firms on A-share stock market.

3.5.1 Distress risk and variation of stock returns

Following Griffin and Lemmon (2002) and Vassalou and Xing (2004), stocks are ranked each June of year t according to their previous December O-score or DLI. To analyze the relation between distress risk (DR) and stock returns, and whether there exist size and value effects on CNAS stock market, the stocks are sorted separately into quintile and decile according to their O-score and DLI (proxies of distress risk), we then examine whether the portfolios with different distress risk provide significantly different returns. A significant difference in the returns would indicate that default risk may be important for the pricing of equities Vassalou and Xing (2004).

The simple sorts of stocks based on their O-score and DLI are presented in Panel A and Panel B of Table 3.3, respectively. In each panel, stocks are firstly divided into five portfolios according to their O-score or DLI, the returns, size, and B/P ratio of portfolios are also shown in the table. Independently, we also sort stocks into 10 portfolios by their O-score or DLI. In Panel A, no matter for the five or the ten O-score portfolios, the results are similar. We find no obvious differences in average returns across the portfolios, and the return difference between the highest DR portfolio and the lowest distress risk portfolio is not statistically significant (0.0029 for the five portfolios with t-stats -1.0688 and 0.0037 for the ten portfolios with t-stats 0.9706). However, it seems that the firm size is negatively related to the distress risk, the higher DR portfolios have smaller size. B/P ratios do not show much differences across the DR quintile or decile except for the highest DR portfolios which have lowest B/P ratio among other DR portfolios.

In Panel B, there is neither significant return difference among the five portfolios, nor the ten portfolios sorted by DLI (-0.0028 for the five DLI-sorted portfolios with t-stats -0.7907 and -0.0038 for the ten DLI-sorted portfolios with t-stats -0.9025). Different from portfolios that sorted by O-score, the trend of size-change is ruleless, but consistent with the results of Vassalou and Xing (2004), the B/P ratio of portfolios increases for both sorts with their default probability (proxy by DLI) increases.

Since the non-significant return differences among the portfolios sorted by both O-score and DLI, we cannot confirm that distress risk has an impact on average stock returns. However, the results reveal that there exist probably size or value effect associated with DR.

Table 3.3 Characteristics of portfolios sorted by O-score and DLI (2005-2014)

Panel A and Panel B of the table represent characteristics of portfolios sorted by O-score and DLI, respectively. Across the rows are the five quintiles or ten deciles of portfolios sorted according to firm's O-score (Panel A) or DLI (Panel B); the last column reports the return difference between high and low default probability portfolios, numbers in parentheses are the corresponding t-statistics at 5% confidence level. Across the rows are the portfolios' average return, O-score (Panel A) or DLI (Panel B), size, and B/P ratio, separately. The unit of firm size is 100 million yuan, the values of DLI are reported in percentage values for easy reading.

Default Probability	Low DP	2	3	4	5	6	7	8	9	High DP	High-Low
Panel A: Characteristics of portfolios sorted by O-score											
Return	0.0228	0.0226	0.0226	0.0223	0.0258						0.0029 (1.0688)
O-score	-2.0799	-0.5225	0.3394	1.1449	3.8525						
Size	10614	12141	7242	6296	3587						
B/P	0.4293	0.4522	0.4695	0.4709	0.3540						
Return	0.0224	0.0233	0.0220	0.0232	0.0228	0.0224	0.0224	0.0223	0.0253	0.0261	0.0037 (0.9706)
O-score	-2.7923	-1.3728	-0.7618	-0.2833	0.1293	0.5500	0.9396	1.3501	1.8953	3.7335	
Size	9515	11669	13706	10548	8203	6283	7045	5547	4675	2433	
B/P	0.4139	0.4441	0.4482	0.4563	0.4700	0.4688	0.4843	0.4575	0.4128	0.2725	
Panel B: Characteristics of portfolios sorted by DLI											
Return	0.0248	0.0256	0.0234	0.0242	0.0220						-0.0028 (-0.7907)
DLI (%)	0.0161	0.1735	0.5499	1.4092	6.4096						
Size	7950	8227	7309	7098	8012						
B/P	0.3456	0.3853	0.4201	0.4560	0.5296						
Return	0.0256	0.0240	0.0264	0.0247	0.0240	0.0227	0.0242	0.0243	0.0222	0.0219	-0.0038 (-0.9025)
DLI (%)	0.0021	0.0299	0.1107	0.2363	0.4207	0.6798	1.0816	1.7365	3.0395	9.7876	
Size	7156	8736	9877	6579	6522	8097	7350	6841	7098	8928	
B/P	0.3270	0.3641	0.3806	0.3901	0.4136	0.4266	0.4444	0.4677	0.5102	0.5490	

3.5.2 Size effect

In order to examine whether there exists size effect across the distress risk groups, we implement the two-way sorts the way Vassalou and Xing (2004) do, stocks are first sorted into five quintiles based on their O-score or DLI (distress risk), then within each DR groups, stocks are sorted into five size groups according to their total market capitalization. Furthermore, we also examine the size effect across the whole sample by sorting all stocks into five size quintiles.

The results of the 25 O-score/Size portfolios are presented in Table 3.4, across the columns are the five DR quintiles, and across the rows are the five size quintiles. The average portfolio returns, size, B/P ratio and O-score are displayed respectively in Panel A, B, C and D. The results in Panel A suggest that there are significant size effects across each DR quintile, the strongest effect is in the group of highest DR with return difference between small and big size portfolios of 0.0194 (with t-stats 3.7498 at 5% confidence level). And we also find the size effect across our whole sample with return difference of 0.0159 (t-stats 3.1086).

The results in Panel B show that across each size quintile, the DR of firms increases with the size decreases apart from the lowest O-score portfolios, consistent with our findings in Table 3.3, the smaller size firms tend to have higher default probabilities. From Panel D, we cannot tell obvious variations within the DR quintiles; only within the highest DR quintile, the smallest size portfolio has the highest O-score, while the biggest size portfolio has the lowest O-score. Panel C indicates that within each size quintile, portfolios with highest DR tend to have lower B/P ratio at least for the three smaller size quintiles, but it is not clear that whether B/P ratio is related to DR directly from this analysis, we will carry out the analysis of value effect subsequently.

To examine whether the size effect controlled by distress risk which estimated using market-based method (DLI) is distinct from that controlled by O-score, we proceed the same steps above except the stocks are first sorted into five portfolios based on their DLI instead of O-score, then within each DLI quintiles stocks are sorted into five size groups, the results are shown in Table 3.5. The same results are found in Panel A that across each DR quintiles, average return of portfolio decreases as the firm size increases, and there exist strong size effect across each DR quintile (the return differences are all statistically significant at 5% confidence level). The strongest effect still is in the highest DR groups (return difference is 0.0180 with t-stats 3.3040). The relationship between DR and size seems chaotic (Panel B) except the two small size quintiles, within which the size increases as DR increases. Panel C of Table 3.5 shows no explicit relationship between B/P ratio and

Table 3.3 Size effect controlled by distress risk (O-score as proxy), 2005-2014

This table presents the results of size effect controlled by distress risk proxy by O-score on Chinese A-share stock market during 2005 to 2014. Stocks are first sorted into five O-score quintiles and then within each O-score portfolio, stocks are sorted into five size quintiles based on their market capitalization, thus we have got 25 O-score/Size portfolios. The average returns, size, B/P ratio and O-score of 25 portfolios are listed in Panel A, B, C, and D respectively. Across the rows of each panel are the five size quintiles, and across the columns of each panel are five O-score quintiles. The unit of size is 100 million 'yuan'.

DR	Size					
	Small	2	3	4	Big	Small-Big
Panel A: average return						
Low-O	0.0296	0.0258	0.0216	0.0197	0.0150	0.0146 (**2.5876**)
2	0.0284	0.0250	0.0225	0.0209	0.0151	0.0133 (**2.6192**)
3	0.0290	0.0246	0.0208	0.0220	0.0154	0.0136 (**2.6722**)
4	0.0316	0.0266	0.0182	0.0161	0.0190	0.0126 (**2.1924**)
High-O	0.0368	0.0296	0.0218	0.0225	0.0174	0.0194 (**3.7498**)
Whole sample	0.0327	0.0260	0.0231	0.0201	0.0169	0.0159 (**3.1086**)
Panel B: size						
Low-O	1399	2397	3765	6769	39072	
2	1417	2415	3691	6434	46965	
3	1378	2247	3433	5912	23318	
4	1300	2119	3135	5312	19770	
High-O	958	1484	2100	3264	10170	
Panel C: B/P ratio						
Low-O	0.4693	0.4961	0.4400	0.3805	0.3581	
2	0.4701	0.4693	0.4586	0.4295	0.4331	
3	0.4385	0.5049	0.4778	0.4685	0.4566	
4	0.4339	0.4828	0.4699	0.4747	0.4921	
High-O	0.2640	0.3148	0.3615	0.3835	0.4218	
Panel D: O-score						
Low-O	-2.2624	-1.9399	-2.0330	-1.9983	-2.0299	
2	-0.5313	-0.5229	-0.5187	-0.5239	-0.5201	
3	0.3583	0.3522	0.3299	0.3379	0.3188	
4	1.1629	1.1415	1.1554	1.1431	1.1221	
High-O	3.3834	2.6381	2.6904	2.2988	2.0960	

Table 3.4 Size effect controlled by distress risk (DLI as proxy), 2005-2014

This table presents the results of size effect controlled by distress risk proxy by DLI on Chinese A-share stock market during 2005 to 2014. Stocks are first sorted into five DLI quintiles and then within each DLI quintile, stocks are sorted into five size quintiles based on their market capitalization, thus we have got 25 DLI/Size portfolios. The average returns, size, B/P ratio and DLI of 25 portfolios are listed in Panel A, B, C, and D respectively. Across the rows of each panel are the five size quintiles, and across the columns of each panel are five DLI quintiles. The values of DLI are percentage values, and the unit of size is 100 million 'yuan'.

DR	Size					
	Small	2	3	4	Big	Small-Big
Panel A: average return						
Low-DLI	0.0323	0.0289	0.0250	0.0209	0.0160	0.0163 (**3.1322**)
2	0.0323	0.0259	0.0248	0.0229	0.0207	0.0116 (**2.1045**)
3	0.0289	0.0270	0.0243	0.0196	0.0162	0.0127 (**2.3553**)
4	0.0328	0.0260	0.0259	0.0182	0.0167	0.0160 (**3.1280**)
High-DLI	0.0339	0.0220	0.0194	0.0183	0.0159	0.0180 (**3.3040**)
Panel B: size						
Low-DLI	1160	1919	3024	5102	28769	
2	1219	1922	2819	4587	30812	
3	1223	1905	2797	4718	26083	
4	1259	2013	2947	5024	24415	
High-DLI	1477	2412	3714	6357	26289	
Panel C: B/P ratio						
Low-DLI	0.3775	0.3898	0.3675	0.3129	0.2799	
2	0.4017	0.4126	0.3923	0.3720	0.3477	
3	0.3926	0.4443	0.4386	0.4217	0.4033	
4	0.4192	0.4715	0.4768	0.4578	0.4548	
High-DLI	0.4710	0.5367	0.5409	0.5371	0.5623	
Panel D: DLI (%)						
Low-DLI	0.0153	0.0205	0.0178	0.0124	0.0142	
2	0.1712	0.1674	0.1843	0.1716	0.1730	
3	0.5558	0.5494	0.5640	0.5399	0.5411	
4	1.3873	1.3848	1.4036	1.4245	1.4464	
High-DLI	5.4074	5.9529	6.3253	6.4563	7.9216	

distress risk, but within each size quintile, the portfolio with highest DR seems has the higher B/P ratio. The most obvious variation is across the highest DR group in panel D, the highest distress risk belongs to the big size portfolio (Big-5). Overall, average returns are closely related to firm size in both Table 3.4 and Table 3.5. it appears that there exists strong size effect across DR group and in the whole sample as well, no matter the proxy for DR is O-score or DLI. This finding is consistent with our empirical results in Chapter 1. However, the relation between size (or B/P ratio) and DR is kind of chaotic and not easy to distinguish from the size effect tests controlled by DR.

3.5.3 Value effect

Similar to the analysis of size effect, to examine the value effect across the DR groups, stocks are first sorted into five DR quintiles and within each DR quintile, the stocks are sorted into five B/P groups. Across the rows of Table 3.6 are the five B/P quintiles and across the columns are the five O-score quintiles. In Panel A, we find the return difference between the highest B/P quintile and the lowest B/P quintile neither significant for all of the five DR portfolios nor significant across the whole sample, which indicates that there exists probability no value effect controlled by distress risk on CNAS stock market during the research period.

In Panel B, the relationship between B/P ratio and DR is not clear. The DR is negatively related to firm size within the lowest B/P quintile (Panel C). In Panel D, across each DR quintile, the relationship between O-score and B/P ratio is not clear except for the lowest and highest DR portfolios. Across the lowest DR quintile, it seems that with tiny change of O-scores, higher B/P ratio associated with higher O-score; but across the quintile which has the highest DR, the higher the B/P ratio the lower O-score of portfolios, exceptionally, the portfolio with lowest B/P ratio has the highest DR (with O-score 3.1856).

The results of value effect controlled by distress risk which is proxy by DLI are displayed in Table 3.7. Notice that in Panel A, same as Table 3.6, none of the return difference across the five DLI quintile is significant. In Panel B, within each B/P quintile, higher DLI (DR) portfolios tend to have higher B/P ratio. In panel D, the DLI of portfolio increases as the B/P ratio increase in the highest DR quintile except for the lowest B/P portfolio.

Table 3.5 Value effect controlled by distress risk (O-score as proxy)

This table presents the results of value effect controlled by distress risk proxy by O-score on Chinese A-share stock market during 2005 to 2014. Stocks are first sorted into five O-score quintiles and then within each O-score quintile, stocks are sorted into five B/P quintiles based on their book-to-price ratio, thus we have got 25 O-score/B/P portfolios. The average returns, B/P ratio size, and O-score of 25 portfolios are listed in Panel A, B, C, and D respectively. Across the rows of each panel are the five B/P ratio quintiles, and across the columns of each panel are five O-score quintiles. The unit of the size is 100 million yuan.

DR	B/P ratio					
	Low-B/P	2	3	4	High-B/P	High-Low
			Panel A: average return			
Low-O	0.0230	0.0206	0.0237	0.0243	0.0217	-0.0013 (-0.2722)
2	0.0177	0.0246	0.0245	0.0228	0.0229	0.0052 (1.4291)
3	0.0200	0.0253	0.0234	0.0215	0.0226	0.0026 (0.7053)
4	0.0201	0.0205	0.0232	0.0238	0.0227	0.0026 (0.5363)
High-O	0.0216	0.0253	0.0249	0.0278	0.0253	0.0037 (0.8270)
Whole sample	0.0220	0.0248	0.0245	0.0253	0.0237	0.0017 (0.4963)
			Panel B: B/P ratio			
Low-O	0.1723	0.2929	0.3923	0.5109	0.7808	
2	0.1921	0.3159	0.4150	0.5390	0.8007	
3	0.1879	0.3252	0.4322	0.5632	0.8399	
4	0.1901	0.3221	0.4245	0.5551	0.8649	
High-O	0.0809	0.2076	0.3203	0.4471	0.7178	
			Panel C: size			
Low-O	14998	8727	6297	10278	11381	
2	8873	12183	9712	15495	14865	
3	8497	5994	7845	6364	7379	
4	6116	5952	5638	5787	7842	
High-O	2565	3507	3981	4125	5225	
			Panel D: O-score			
Low-O	-2.3082	-2.0629	-2.0357	-1.9592	-1.9006	
2	-0.5188	-0.5231	-0.5225	-0.5127	-0.5454	
3	0.3479	0.3297	0.3343	0.3387	0.3445	
4	1.1593	1.1657	1.1459	1.1256	1.1352	
High-O	3.1856	2.4067	2.2171	2.1017	2.0868	

Table 3.6 Value effect controlled by distress risk (DLI as proxy)

This table presents the results of size effect controlled by distress risk proxy by DLI on Chinese A-share stock market during 2005 to 2014. Stocks are first sorted into five DLI quintiles and then within each DLI quintile, stocks are sorted into five size quintiles based on their market capitalization, thus we have got 25 DLI/Size portfolios. The average returns, size, B/P ratio and DLI of 25 portfolios are listed in Panel A, B, C, and D respectively. Across the rows of each panel are the five size quintiles, and across the columns of each panel are five DLI quintiles. The value of DLI is percentage value and the unit of the size is 100 million yuan.

	B/P ratio					
DLI	Low-B/P	2	3	4	High-B/P	High-Low
			Panel A: average return			
Low-DLI	0.0218	0.0234	0.0256	0.0265	0.0261	0.0043 (1.1785)
2	0.0219	0.0242	0.0262	0.0297	0.0251	0.0032 (0.9650)
3	0.0196	0.0257	0.0224	0.0237	0.0249	0.0052 (1.6248)
4	0.0220	0.0228	0.0241	0.0267	0.0250	0.0030 (0.9643)
High-DLI	0.0243	0.0222	0.0206	0.0203	0.0225	-0.0018 (-0.4368)
			Panel B: B/P ratio			
Low-DLI	0.1317	0.2355	0.3256	0.4178	0.6188	
2	0.1610	0.2736	0.3570	0.4559	0.6812	
3	0.1769	0.2999	0.3909	0.4984	0.7365	
4	0.1927	0.3306	0.4278	0.5427	0.7887	
High-DLI	0.2249	0.3736	0.4893	0.6337	0.9287	
			Panel C: size			
Low-DLI	11341	7380	5650	9375	5955	
2	6785	5533	7639	6090	15186	
3	7068	7924	6777	6988	7762	
4	6366	7909	6760	5386	9096	
High-DLI	7459	7905	7956	7192	9554	
			Panel D: DLI (%)			
Low-DLI	0.0105	0.0127	0.0190	0.0174	0.0206	
2	0.1682	0.1721	0.1765	0.1777	0.1731	
3	0.5299	0.5535	0.5551	0.5553	0.5557	
4	1.3922	1.3736	1.3849	1.4307	1.4652	
High-DLI	6.2900	5.7332	6.5571	6.6960	6.7771	

We summarize that there exists strong size effect but no value effect, however, the robust size effect and lack of value effect are robust when controlled by distress risk as well as for the whole sample on CNAS stock market from 2005 to 2014. And the effects are also robust to the different proxies for distress risk. Nevertheless, the relationship between size and DR, and B/P ratio and DR are quite confusing. The most distinct is that B/P ratio is positively related to DR that use DLI as proxy (Panel B of Table 3.7), portfolios with higher DLI have higher B/P ratio.

3.6 Augmented four-factor model and empirical evidence

In order to investigate whether FF three factors are proxies for distress risk, we examine an augmented four-factor model, which include market factor (market premium), size factor (SMB), value factor (HML) and distress risk factor (DRF). If all the priced information in SMB and HML is related to financial distress risk, we would expect to find that in the presence of DRF, SMB and HML lose all their ability to explain equity returns[44]. In particular, we use both accounting-based model and market-based model as proxy for distress risk to investigate whether different methods of estimating default probability cause different results.

3.6.1 Augmented four-factor model

We add a distress risk factor on the basis of FF3F model to form the augmented four-factor model:

$$R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + d_i DRF + \varphi_{i,t} \tag{3.18}$$

where DRF is our mimicking portfolio, distress risk factor, d_i is the regression coefficient of *DRF*, and $\varphi_{i,t}$ is the error term for portfolio *i* at time *t.*

DRF is constructed separately using O-score and DLI as proxy for distress risk, denoted as $\mathrm{DRF}_{\mathrm{O-score}}$ and $\mathrm{DRF}_{\mathrm{DLI}}$, the summary statistics of four factors are shown in Table 3.8 Panel A presents the statistic description of four factors, the time-series mean of market premium (0.0024), SMB (0.0119) and $\mathrm{DRF}_{\mathrm{O-score}}$ (0.0010) are positive, while that of HML (-0.0020)

[44] Vassalou and Xing (2004)

Table 3.7 Summary statistics of four factors: market factor, SMB, HML and distress risk factor (July 2005 to May 2015)

This table presents summary statistics of four factors, market factor, size factor, value factor and distress risk factor ($\mathrm{DRF_{O-score}}$ or $\mathrm{DRF_{DLI}}$). Statistic description of these factors are shown in Panel A and the correlation matrix among these factors is presented in Panel B.

	$R_M - R_f$	SMB	HML	$\mathrm{DRF_{O-score}}$	$\mathrm{DRF_{DLI}}$
Panel A Statistic description of four factors					
Mean	0.0024	0.0119	-0.0020	0.0010	-0.0026
Standard Error	0.0083	0.0038	0.0030	0.0019	0.0030
t-statistic	0.2892	3.1316	-0.6667	0.5263	-0.8667
Median	0.0064	0.0137	-0.0057	0.0011	-0.0014
S.D.	0.0905	0.0414	0.0329	0.0206	0.0326
Sample Variance	0.0082	0.0017	0.0011	0.0004	0.0011
Kurtosis	1.1923	2.3341	4.0778	-0.2535	2.0064
Skewness	-0.7299	-0.7784	0.5098	0.2176	0.1691
Panel B Correlation matrix of four factors					
RM-RF	1				
SMB	-0.0175	1			
HML	0.1985	-0.3246	1		
$\mathrm{DRF_{O-score}}$	0.2362	0.2806	0.3672	1	
$\mathrm{DRF_{DLI}}$	0.4040	-0.2983	0.7139	0.6665	1

and $\mathrm{DRF_{DLI}}$ (-0.0026) are negative. The only significant t-stats is from SMB, and the size factor is most likely to be priced in equity returns.

The correlation matrix of the four factors in Panel B indicate that the two DRF factors are highly correlated (with correlation coefficient 0.6665), which means that $\mathrm{DRF_{O-score}}$ and $\mathrm{DRF_{DLI}}$ may contain most of the same information. It is worth noting that $\mathrm{DRF_{DLI}}$ and HML are highly positive correlated, the component of equity returns that each factor explains may be similar.

3.6.2 Time-series regressions analysis

We carry out the TSRs of the augmented four-factor model on CNAS stock market in this section. To construct distress risk factor, we apply both accounting-based model and market-based model to estimating default probability of stocks.

3.6.2.1 Accounting-based distress risk factor and regression results

Table 3.8 shows the summary statistics of 18 portfolios sorted on Size, B/P and O-score. For all the 18 portfolios, the average excess returns are lower for small size portfolios while higher for big size portfolios, which is consistent with the size effect conclusion that equity return is negatively related to firm size, the big size portfolios tend to have lower average returns. However, we find no obvious relationship between average excess returns and B/P ratio or distress risk proxy by O-score, except the highest B/P portfolios with small size (across the highest B/P group, the higher DR portfolio tends to have higher average excess return) and the lowest DR portfolios with small size (across the lowest DR portfolios, higher B/P portfolio tends to have lower average excess return, which is inconsistent with FF's findings that average stock returns are positively related to B/M ratio). The results of Table 3.9 also reveal that distress risk is related to firm size, regarding to the size parts, the higher DR portfolios always have smaller size (except the portfolio SH1), meanwhile, regarding to the O-score parts, the big size portfolios have lower O-score than the small size portfolios excluding the lowest DR groups. Whereas, it is not easy to tell the relationship between B/P ratio and O-score from the analysis so far.

To investigate how the four factors, explain average excess returns of 18 SBPO sorted portfolios, we following perform the TSRs and the results are presented in Table 3.9. The left-hand part presents the regression coefficients and adjusted R-squares, while the right-hand part presents the corresponding t-statistics corrected for heteroscedasticity and autocorrelation using Newey-West estimator with five lags and the residual standard error. As always, the coefficients of excess market return and SMB are all highly significant at 5% confidence level, and there exists size effect. Regression coefficients $\beta(h)$ increase as B/P ratio increase, but the loadings on HML seem only to be significant within the highest B/P groups (for small size portfolios and big size portfolios) and the lowest B/P group (for big size portfolios). Loadings on DRF $\beta(d)$ increase as O-score increase except for the portfolio group with small size and medium B/P ratio, but the significant coefficients mainly exist in the lowest (for big size portfolios) and highest (for small size and big size portfolios) O-score groups. Comparing with the regressions on FF3F model of the same 18 portfolios (Appendix F), the TSR coefficients of FF three factors do not have a noteworthy difference with or without an augmented factor DRF in addition to FF3F model. Adding a DRF factor (with averaged adjusted R-square 0.8990) does not change markedly the time-series explanatory power of FF three factors (with averaged adjusted R-square 0.8939).

Table 3.8 Summary statistics of 18 (2x3x3) Size-B/P-O-score sorted portfolios (July 2005-May 2015)

The 18 portfolios are constructed from the intersection of three independent sorts of all stocks into two size, three B/P and three DR portfolios. DR is estimated by O-score. The table has two parts: small size and big size, and in each part, average excess returns, firm numbers, size, B/P ratio and O-score of 18 portfolios are presented. Across the rows are the three B/P portfolios (L, M and H), and across the columns are the three O-score portfolios (O1, O2 and O3). The unit of size is 100 million 'yuan'.

O-score	B/P ratio					
	L	M	H	L	M	H
			Small size			
	Average excess returns			Firm numbers		
O1	0.0190	0.0170	0.0154	24	55	49
O2	0.0129	0.0165	0.0161	41	76	73
O3	0.0153	0.0174	0.0173	79	63	46
	Size			B/P ratio		
O1	1874	1875	1887	0.2161	0.3970	0.6941
O2	1804	1849	1939	0.2090	0.3955	0.6958
O3	1619	1800	1889	0.1675	0.3869	0.6824
	O-score					
O1	-1.8157	-1.5943	-1.5123			
O2	0.3383	0.3118	0.3212			
O3	2.5651	1.8517	1.7261			
			Big size			
	Average excess returns			Firm numbers		
O1	0.0078	0.0086	0.0066	72	74	56
O2	0.0090	0.0102	0.0059	69	89	94
O3	0.0072	0.0063	0.0095	46	51	45
	Size			B/P ratio		
O1	14595	14823	25960	0.2035	0.3924	0.7028
O2	11436	11108	13714	0.2112	0.3977	0.7284
O3	7681	8297	8762	0.1877	0.3957	0.7198
	O-score					
O1	-1.7393	-1.5941	-1.5076			
O2	0.2410	0.2565	0.2837			
O3	1.9355	1.6339	1.6183			

Table 3.9 Time-Series Regressions of 18 Size-B/P-O-score sorted portfolios on augmented four-factor model (July 2005-May 2015)

This table reports the time-series regression results for 18 portfolios formed on size, B/P ratio and O-score. The stocks are divided into two size groups based on the breakpoint of median market capitalization, and the breakpoints for the three B/P groups are the top 30%, median 40% and bottom 30% of B/P ratio, similarly as B/P groups, the stocks are divided into three groups based on their O-score (O1, O2 and O3, represent the low, medium and high O-score separately). The intersection of two size groups, three B/P groups and O-score groups form 18 portfolios. The left part of the table is the coefficients of time-series regressions and adjusted R-square, the right part is the corresponding t-stats corrected for heteroscedasticity and autocorrelation using Newey-West estimator and residual standard error, and the numbers in bold are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + d_i DRF_{O\text{-}score} + \varphi_{i,t}$

Small size						
O-score	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
O1	0.0000	-0.0016	-0.0043	0.0003	-0.6528	-1.5354
O2	-0.0070	-0.0020	-0.0018	-1.9398	-0.9184	-0.6258
O3	-0.0047	-0.0003	0.0006	-1.7372	-0.1185	0.2581
		b			*t* (*b*)	
O1	0.9835	1.0019	0.9784	**18.1800**	**20.2270**	**21.1813**
O2	1.0186	0.9969	1.0041	**19.9062**	**23.4918**	**17.6368**
O3	0.9647	0.9710	0.9754	**22.3848**	**22.0340**	**18.9126**
		s			*t* (*s*)	
O1	1.4076	1.3903	1.5692	**10.6830**	**11.8585**	**13.3027**
O2	1.4445	1.3948	1.3712	**11.2147**	**13.6715**	**10.6478**
O3	1.3875	1.2284	1.1975	**11.4363**	**11.7114**	**10.4843**
		h			*t* (*h*)	
O1	-0.1103	0.1326	0.5809	-0.6975	0.9491	**3.6733**
O2	-0.0190	0.2152	0.4466	-0.1134	1.6752	**2.8900**
O3	-0.0932	0.0641	0.3075	-0.6026	0.5211	**2.1046**
		d			*t* (*d*)	
O1	-0.2854	-0.0707	-0.1270	-1.4096	-0.4613	-0.8243
O2	0.2218	-0.1139	0.0635	1.6652	-0.7966	0.3578
O3	0.8797	0.8008	0.6211	**6.7380**	**7.0318**	**3.4913**
		Adj R-square			Residual standard error	
O1	0.8684	0.9114	0.9033	0.0403	0.0330	0.0356
O2	0.9002	0.9175	0.9024	0.0368	0.0316	0.0354
O3	0.9233	0.9199	0.9067	0.0320	0.0318	0.0342

Table 3.9 Continued

Big size						
O-score	B/P ratio					
	L	M	H	L	M	H
	a			*t* (*a*)		
O1	-0.0022	-0.0034	-0.0047	-0.9766	-1.2719	-1.8308
O2	-0.0038	-0.0004	-0.0045	-1.2982	-0.1281	-1.7928
O3	-0.0054	-0.0060	-0.0001	-1.7151	-2.0373	-0.0473
	b			*t* (*b*)		
O1	0.9715	1.0489	1.0288	**18.0644**	**19.9291**	**18.9004**
O2	1.0192	1.0881	1.0399	**18.1832**	**20.2544**	**17.9173**
O3	1.0165	1.1039	1.0602	**16.4040**	**17.4080**	**24.4310**
	s			*t* (*s*)		
O1	0.6021	0.8563	0.8358	**5.3909**	**6.8872**	**8.3814**
O2	0.8453	0.6659	0.7390	**7.1385**	**5.1131**	**6.2367**
O3	0.7488	0.7823	0.6491	**5.7002**	**6.0745**	**5.8866**
	h			*t* (*h*)		
O1	-0.4976	0.0938	0.5270	**-3.4900**	0.6492	**4.2189**
O2	-0.2723	0.0177	0.5810	-1.7387	0.1078	**3.7957**
O3	-0.4012	0.0356	0.6480	**-2.5041**	0.2226	**4.9922**
	d			*t* (*d*)		
O1	-0.4896	-0.4684	-0.0989	**-3.9778**	**-3.5396**	-0.8279
O2	-0.2171	0.0833	0.2654	-1.4397	0.5639	**2.2562**
O3	0.4937	0.3375	0.5305	**3.0586**	1.9698	**3.1082**
	Adj R-square			Residual standard error		
O1	0.8744	0.8848	0.9061	0.0336	0.0354	0.0324
O2	0.8752	0.8928	0.9090	0.0364	0.0354	0.0329
O3	0.8592	0.8796	0.9166	0.0402	0.0395	0.0326

Thus we conclude that there exists distress risk effect, since portfolios with higher O-score associated with higher return. The DRF constructed using O-score as proxy for DR has explanatory power in time-series stock returns only for the portfolios with extreme DR (lowest DR or highest DR). Whereas, the augmented DRF add limited explanatory power in explaining stock returns, and FF factors are not proxy for distress risk in explaining time-series variations of average stock returns, at least when the DRF is constructed using O-score to estimate financial distress risk. We then perform the same TSRs using DLI as proxy for DR.

3.6.2.2 Market-based distress risk factor and regression results

In order to test whether different methods for predicting distress risk affect the empirical results, we proceed the Merton's option-pricing model (market-based model) in predicting default probability, which is later applied by Vassalou and Xing (2004). Vassalou and Xing denote Merton's default probability as DLI (Default Likelihood Indicator), follow which we calculate the default probability of CNAS stocks.

Table 3.10 displays the summary statistics of 18 SBPD sorted portfolios, the structure of the table is similar to Table 3.8 except the proxy for distress risk is DLI instead of O-score. Not surprisingly that average excess returns are negatively related to firm size, however, the relationship between average excess return and B/P ratio or DLI is chaotic. The relationship between size and DLI is not as clear as that between size and O-score, while it seems that B/P ratio increases as DLI increases except the portfolio SL1. Next, we will implement the TSRs to investigate how the four factors explain average excess returns and to figure out the relationship among stock returns, size, B/P ratio and distress risk.

The TSRs' results on the augmented four-factor model of 18 SBPD sorted portfolios are reported in Table 3.11. It shows pretty much the same results as that of 18 SBPO sorted portfolios in Table 3.9. All the regression coefficients for excess market return and SMB are highly significant, and excess stock returns are negatively related to firm size. Exceptionally, $\beta(d)$, the coefficients of DRF_{DLI}, are significant for both the lowest DLI portfolios (with negative loadings) and the highest DLI portfolios (with positive loadings), consistent with Vassalou and Xing (2004), we find positive relationship between excess stock returns and distress risk on Chinese market, but only in the lowest or (and) highest DR (DLI) portfolios. Our results are contrary to some literature[45] that conclude the high default risk is not rewarded by higher returns. Comparing with the TSRs on FF3F model of the same 18 SBPD portfolios (Appendix F), in the presence of augmented DRF (DLI as proxy for DR), FF factors do not lose their explanatory power, however, the four-factor model indeed capture slightly more variation of the 18 SBPD sorted portfolios' return (with average adjusted R-square 0.9027) than the original FF3F Model (with average adjusted R-square 0.8980).

We can conclude that the excess market returns and size factor SMB are always highly positively related to excess average stock returns, and big size stocks always have lower average returns. The value factor HML also has explanatory power in explaining the time-series average stock returns, but only exist in the extreme (lowest or highest) B/P groups. In addition, there exists significant distress risk effect on CNAS stock market over the sample

[45] Dichev (1998), Griffin and Lemmon (2002) and Lin and Chen (2008), etc.

Table 3.10 Summary statistics of 18 (2x3x3) Size-B/P-DLI sorted portfolios

The 18 portfolios are constructed from the intersection of three independent sorts of all stocks into two size, three B/P and three DR (proxy by DLI) portfolios. DR in this table is proxy by DLI. The table has two parts: small size and big size, and in each part, average excess returns, firm numbers, size, B/P ratio and DLI of 18 portfolios are presented. Across the rows are the three B/P portfolios (L, M and H), and across the columns are the three DLI portfolios (D1, D2 and D3). The DLI is percentage value, and the unit of size is 100 million 'yuan'.

DLI	B/P ratio					
	L	M	H	L	M	H
			Small size			
	Average excess returns			Firm numbers		
D1	0.0176	0.0201	0.0176	70	104	52
D2	0.0135	0.0173	0.0188	80	136	94
D3	0.0206	0.0189	0.0160	37	73	82
	Size			B/P ratio		
D1	1797	1735	1712	0.2016	0.3924	0.6429
D2	1748	1815	1838	0.1992	0.3934	0.6573
D3	1767	1871	1956	0.1955	0.3944	0.7034
	DLI (%)					
D1	0.0432	0.0510	0.0612			
D2	0.5721	0.6073	0.6332			
D3	4.4861	3.8763	4.5588			
			Big size			
	Average excess returns			Firm numbers		
D1	0.0110	0.0096	0.0072	118	74	32
D2	0.0075	0.0102	0.0090	98	118	74
D3	0.0087	0.0064	0.0065	45	91	120
	Size			B/P ratio		
D1	12069	15431	33975	0.1951	0.3856	0.6680
D2	10399	13418	14494	0.2113	0.3930	0.6913
D3	11296	11844	11611	0.2185	0.4021	0.7384
	DLI (%)					
D1	0.0419	0.0454	0.0615			
D2	0.5209	0.6115	0.6679			
D3	4.5184	4.9209	5.7250			

Table 3.11 Time-Series Regressions of 18 Size-B/P-DLI sorted portfolios on augmented four factor model (July 2005-May 2015)

In this table, the time-series regressions' results for 18 portfolios formed on size, B/P ratio and DLI are presented. The stocks are divided into two size groups based on the breakpoint of median market capitalization, and the breakpoints for the three B/P groups are the top 30%, median 40% and bottom 30% of B/P ratio (named Low, Medium and High), similarly as B/P groups, the stocks are divided into three groups based on their DLI (named D1, D2, and D3, represent the low, medium and high DLI separately). The intersection of two size groups, three B/P groups and DLI groups form 18 portfolios. The left part of the table is the coefficients of time-series regressions and adjusted R-square, the right part is the relative t-statistics corrected for heteroscedasticity and autocorrelation using Newey-West estimator and residual standard error, and the numbers in bold are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + d_i DRF_{DLI} + \varphi_{i,t}$

Small size						
DLI	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
D1	-0.0029	-0.0005	-0.0039	-1.0573	-0.1862	-1.1439
D2	-0.0077	-0.0020	-0.0007	**-2.5693**	-0.9118	-0.2556
D3	0.0024	0.0011	-0.0007	0.7513	0.4257	-0.2726
		b			*t* (*b*)	
D1	1.0080	1.0205	1.0038	**20.9669**	**22.5534**	**22.0400**
D2	0.9851	1.0132	1.0201	**21.8739**	**23.4259**	**20.7465**
D3	0.9412	0.9777	0.9626	**20.7408**	**29.0933**	**18.9405**
		s			*t* (*s*)	
D1	1.4325	1.4235	1.5812	**17.0791**	**13.0447**	**13.8918**
D2	1.6249	1.4059	1.4706	**14.8188**	**16.0954**	**12.1920**
D3	1.4806	1.4054	1.3504	**14.7955**	**15.2163**	**12.7115**
		h			*t* (*h*)	
D1	-0.0995	0.1619	0.7386	-0.5584	0.9116	**3.7294**
D2	-0.1802	0.0882	0.3894	-1.0067	0.6316	**2.1180**
D3	-0.2696	-0.0647	0.1716	-1.5502	-0.4668	0.9373
		d			*t* (*d*)	
D1	-0.2688	-0.4577	-0.5041	**-2.1132**	**-3.1580**	**-3.1573**
D2	0.2716	-0.0927	-0.1000	**2.0505**	-0.8700	-0.6824
D3	0.6708	0.4422	0.4337	**5.2632**	**4.0964**	**3.4228**
		Adj R-square			Residual standard error	
D1	0.9191	0.9138	0.9065	0.0317	0.0327	0.0350
D2	0.9228	0.9283	0.9082	0.0325	0.0298	0.0348
D3	0.8985	0.9265	0.9147	0.0365	0.0304	0.0325

Table 3.11 Continued

Big size						
DLI	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
D1	-0.0010	-0.0039	-0.0053	-0.4195	-1.6124	-1.7204
D2	-0.0052	-0.0023	-0.0022	-1.8547	-0.8540	-0.8066
D3	-0.0021	-0.0044	-0.0032	-0.6841	-1.5073	-1.5033
		b			*t* (*b*)	
D1	0.9920	1.0514	0.9435	**19.6819**	**24.5412**	**16.7052**
D2	1.0288	1.1002	1.0605	**16.2234**	**21.3147**	**23.2151**
D3	1.0576	1.0880	1.0344	**24.3647**	**20.7160**	**21.7020**
		s			*t* (*s*)	
D1	0.5848	0.8023	0.9166	**5.6470**	**7.1406**	**8.0476**
D2	0.8035	0.7937	0.7936	**6.4233**	**7.7667**	**8.6943**
D3	0.7138	0.7723	0.8138	**7.3415**	**5.8087**	**8.7760**
		h			*t* (*h*)	
D1	-0.3030	0.0443	0.5003	**-2.0710**	0.2813	**3.6915**
D2	-0.5414	-0.0845	0.3792	**-3.1207**	-0.4081	**2.2044**
D3	-0.4844	-0.1790	0.4319	**-2.9118**	-0.9566	**2.8856**
		d			*t* (*d*)	
D1	-0.6446	-0.4718	-0.0774	**-5.1570**	**-3.7512**	-0.6858
D2	0.1191	-0.0783	0.0341	0.8120	-0.4959	0.2478
D3	0.3748	0.4312	0.5130	**2.5523**	**2.6643**	**4.7165**
		Adj R-square			Residual standard error	
D1	0.8745	0.8879	0.8678	0.0338	0.0344	0.0367
D2	0.8719	0.8986	0.9098	0.0379	0.0347	0.0324
D3	0.8822	0.8883	0.9287	0.0373	0.0379	0.0300

period, the explanatory power of DRF exists in the extreme top (highest DR) and bottom (lowest DR) portfolio groups. FF factors cannot proxy for DRF, instead, DRF explains average stock returns in combination with FF factors on CNAS stock market. However, the additional explanatory power of DRF is limited. Besides, the distress risk factor constructed based on DLI seems performs better than that constructed based on O-score.

3.6.3 Cross-sectional regressions of the augmented four-factor model

Furthermore, we also conduct the CSRs using FM two-stage approach to examine whether the augmented four-factor model is able of capturing the variation of the cross-sectional average excess stock returns. The CSR formula is as follows:

$$R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB} \hat{s}_i + \gamma_{HML} \hat{h}_i + \gamma_{DRF} \hat{d}_i + \varepsilon_{i,t} \tag{3.19}$$

where, $R_{i,t} - R_f$ is the excess returns of the same 18 Size-B/P-DR sorted portfolios in the TSRs; $\hat{b}_i$, $\hat{s}_i$, $\hat{h}_i$ and $\hat{d}_i$ are the estimated coefficients of the market factor, size factor SMB, value factor HML and distress risk factor DRF obtained from TSRs; γ_M, γ_{SMB}, γ_{HML} and γ_{DRF} are the coefficients of CSRs.

Following equation (3.19), the CSRs are performed each month (119 months, July 2005 to May 2015) by regressing the excess returns of 18 Size-B/P-DR sorted portfolios on the coefficients obtained from the TSRs, thus we have 119 sets of CSR coefficients. The gammas are then calculated by taking the simple average of the 119 sets of CSR coefficients. Similarly, we also report both the FM t-stats and the EIV adjusted t-stats as in previous chapters. And we also examine the four-factor model with DRF estimated based on O-score and DLI, respectively.

In order to examine whether FF factors proxy for DRF in capturing the cross-sectional variation of average stock returns, we perform three kinds of regressions on (1) the augmented four-factor model as presented in equation (3.19); (2) the original FF3F Model; and (3) only excess market return and DRF using 18 Size-B/P-DR (O-score or DLI) portfolios.

The empirical results are reported in Table 3.12, in Panel A, the DR is estimated by O-score, while in Panel B, the DR is measured by DLI. Each panel contains three parts, which report respectively the CSR results of the three kinds of regressions (denoted as R1, R2 and R3) mentioned above. The first row in each part is the average of 119 CSR coefficients, and the corresponding FM t-stats and EIV adjusted t-stats (SH t-stats) are reported in the bracket below the coefficients. The averaged adjusted R-squares are reported in the last columns in percentage values.

The results in both Panel A and Panel B are much the same. No matter regressing the 18 portfolios on only market factor (R3) and DRF (both constructed based on O-score and DLI) or on FF3F Model (R2), loadings on DRF is never an important determinant of average returns. Furthermore, comparing the first two regressions (R1 and R2), FF factors (market

Table 3.12 Cross-sectional regressions of 18 Size-B/P-DR sorted portfolios on augmented four-factor model, on FF3F Model, and on market factor and DRF (July 2005-May 2015, 119 months)

The cross-sectional regression results of 18 Size-B/P-DR sorted portfolios on the augmented four-factor model (R1), on FF3F Model (R2), and on market factor and DRF (R3) are reported in this table. In Panel A the DRF is constructed by O-score sorted portfolios and in Panel B the DRF is constructed by DLI sorted portfolios. Each panel contains three parts (R1, R2, and R3), the first row of each part reports the cross-sectional regressions' intercepts and coefficients (gammas), the second and third rows report the corresponding Fama-MacBeth t-statistics (FM t-stats) and Shanken corrected t-statistics (SH t-stats). The numbers in bold are the t-statistics that are significant at 5% confidence level. The averaged adjusted R-squared are reported in the last column in percentage form.

Regressions1 (R1): $R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB}\hat{s}_i + \gamma_{HML}\hat{h}_i + \gamma_{DRF}\hat{d}_i + \varepsilon_{i,t}$

Regressions2 (R2): $R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB}\hat{s}_i + \gamma_{HML}\hat{h}_i + \varepsilon_{i,t}$

Regressions3 (R3): $R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{DRF}\hat{d}_i + \varepsilon_{i,t}$

	Const.(α)	γ_M	γ_{SMB}	γ_{HML}	γ_{DRF}	Adj. R^2 (%)
Panel A: Cross-sectional regressions on FF3F Model and on DRF (O-score)						
R1	0.0230	-0.0214	0.0101	-0.0002	0.0009	48.92
FM t-stats	(1.8014)	(-1.4530)	(**2.4481**)	(-0.0717)	(0.4641)	
SH t-stats		(**-2.4014**)	(**2.5008**)	-0.0711	0.4622	
R2	0.0255	-0.0236	0.0098	-0.0003		44.05
FM t-stats	(1.9885)	(-1.6110)	(**2.3688**)	(-0.1059)		
SH t-stats		(**-2.6479**)	(**2.4250**)	(-0.1042)		
R3	0.0627	-0.0545			0.0032	35.62
FM t-stats	(**2.6825**)	(**-2.4364**)			(1.4291)	
SH t-stats		(**-5.6066**)			(1.2769)	
Panel B: Cross-sectional regressions on FF3F Model and on DRF (DLI)						
R1	0.0058	-0.0065	0.0127	-0.0025	-0.0026	
FM t-stats	(0.4761)	(-0.4702)	(**3.0848**)	(-0.7622)	(-0.8765)	57.24
SH t-stats		-0.7325	(**3.1387**)	-0.7578	-0.8735	
R2	0.0038	-0.0046	0.0127	-0.0023		
FM t-stats	(0.2963)	(-0.3298)	(**3.0897**)	(-0.7190)		50.39
SH t-stats		(-0.5220)	(**3.1698**)	(-0.7087)		
R3	0.0409	-0.0278			-0.0049	
FM t-stats	(**2.4606**)	(-1.7412)			(-1.5825)	23.07
SH t-stats		(**-2.9414**)			(-1.5804)	

beta and SMB of Panel A, SMB of Panel B) do not lose their explanatory power in the presence of DRF. We might conclude that though DRF is a priced factor in determining time-series average returns, it is not the case in determining cross-sectional average returns on CNAS stock market over the sample period.

The results also indicate that no matter the DRF is constructed using O-score or DLI as proxy, neither value factor HML and distress risk factor DRF is able to capture the cross-sectional variation in average stock returns. The evidence again proves the existence of size premium on CNAS stock market.

3.7 Conclusions

We use both accounting-based model (O-score) and market-based model (DLI) to estimate distress risk and construct a mimicking distress risk factor on CNAS stock market. We first examine whether there exist size effect and value effect controlled by default risk or in the whole sample during our research period in China. The results suggest that there only exists size effect but this effect seems not related to distress risk, and this effect do not depend on the method we use to estimate the distress risk.

Following literature such as Vassalou and Xing that investigate whether the Fama-French factors can be proxy by distress risk factor, we augment FF3F model by adding a mimicking distress risk portfolio (DRF). We examine the variation of excess average returns of 18 Size-B/P-DR sorted portfolios explained by the augmented four-factor model both through time-series and CSRs. From the TSRs, we conclude that the explanatory power of FF three factors do not has significant change with or without the DRF is presented in the model. FF factors cannot proxy for DRF, instead, DRF explains time-series average stock returns combining with FF factors on CNAS stock market; most contributions to the excess average returns of value factor HML and distress risk factor DRF are concentrated in the extreme top or bottom portfolios, and the average returns are positively related to the distress risk. However, the additional explanatory power of DRF is limited. Comparing the regression results by using O-score and DLI as proxy of distress risk, the distress risk factor constructed based on DLI seems performs slightly better than that constructed based on O-score.

We provide evidence from the CSRs that no matter the DRF is constructed using O-score or DLI as proxy, there exists robust size premium (robust market premium when DR is estimated using O-score), neither value factor HML and distress risk factor DRF is able to capture the cross-sectional variation in average stock returns. Thus, FF factors cannot proxy as DRF in the cross-section on CNAS stock market over the sample period.

General conclusions

The main objective of this dissertation is to explore the risk factors and factor models on CNAS stock market based on the context of FF3F Model.

The main results of this dissertation are presented as follows:

- First of all, we re-examine the applicability of FF3F Model considering several special features of Chinese stock market during July 2004 to May 2015. The empirical results show that FF3F Model can explain a majority of time-series variation of the CNAS stock returns during the research period, when using tradable market value to weight the portfolios, total market capitalization to decide the size breakpoint and B/P ratio instead of B/M ratio. The CSRs results are consistent with most of the previous studies on Chinese stock market, market beta and SMB are important determinants in explaining the cross-sectional variation in the average stock returns over the sample period. There exists negative market premium and positive size premium on CNAS stock market, however, we find no value premium during the sample period. Those findings are robust with EIV adjustment and are independent of research interval.

- We also investigate the applicability of the latest FF5F Model on CNAS stock market during the period July 2010 to May 2015. To proceed with this examination, we construct three sets of portfolios, six value-weighted Size-B/P portfolios, six value-weighted Size-OP portfolios and six value-weighted Size-Inv portfolios. For all the three sets of portfolios, the original three factors - market factor, size factor and value factor – still have strong time-series explanatory power for the expected excess returns in the presence of profitability and investment factors. There always exists size effect in all three sets of portfolios and the excess returns are negatively related to firm size; there exists value effect in SBP portfolios, profitability effect in Size-OP portfolios and investment effect in Size-Inv portfolios. The explanatory power of RMW factor only exists in the six Size-OP portfolios. CMA factor explains the average return of portfolios that only in the extreme OP or Inv groups (such as the weak OP group, robust OP group, the aggressive and conservative Inv groups); while the significant loadings on CMA for the Size-B/P portfolios are relatively dispersive.

- Comparing the performance of both FF3F Model and FF5F Model on CNAS stock market, in the presence of profitability and investment factors, FF5F Model seems not capture more variations of expected stock returns than the three-factor model except the six value-weighted portfolios formed on size and operating profitability (though the improvement is limited) on CNAS stock market during the research period July 2010 to May 2015. However, the research period is relatively short in this study, we suggest to apply the examination with longer time interval for the FF5F Model on Chinese stock market in the future.

- We examine in chapter 2 whether FF factors SMB and HML proxy for the innovations of selected state variables (aggregate dividend yield, one-month T-bill rate, term spread and default spread) that describe future investment opportunities on CNAS stock market during the period December 2006 to May 2015. Both time-series and CSRs are performed on five comparative models. The empirical results indicate that FF factors don’t lose their explanatory power with or without the presence of the innovations of selected four state variables in both the time-series and cross-sectional examinations on CNAS stock market over the research period. Evidence from the CSRs also reveals that there are significant market risk premium and size premium. We find the information contained in the innovation of aggregate dividend yields (IDIV) seems totally captured by the combination of market beta and size factor. FF factors might have played a limited role in capturing alternative investment opportunities proxied by innovations of the selected four state variables.

- Since we find that FF factors cannot proxy for innovations of selected state variables on CNAS stock market, for the sake of the meaning behind them, we examine whether FF factors proxy for distress risk factor and compare whether different methods of constructing factors result in the different outcomes. The empirical results suggest that there is no significant evidence that FF factors are proxying for distress risk on CNAS stock market. The presence of DRF has little effect on the time-series explanatory power of FF three factors, instead, DRF can explain partially the time-series excess average stock returns combining with FF three factors. Comparing the TSR results by using two different methods as proxy of distress risk, the distress risk factor constructed based on DLI seems performs slightly better than that constructed based on O-score in capturing time-series average returns. However, DRF is not an important determinant of cross-sectional average returns, and FF factors cannot proxy as DRF in the cross-section on CNAS stock market during our research period July 2005 to May 2015.

Moreover, our studies on the risk factors in China presented in this dissertation have also provided new implications in practice on Chinese stock market:

First of all, considering several special features of Chinese stock market, our results indicate that the market beta and size factor SMB are important determinants of cross-sectional average stock returns. And the existence of size premium and lack of value premium on CNAS stock market seem independent of the research period. Based on those findings of FF3F Model on Chinese stock market, such as asset managers, they can build portfolios that tilt towards the size factor SMB but not the value factor HML so that to gain the size premium. Furthermore, asset managers or the individual investors are able to assess the potential performance of a portfolio relative to the FF3F Model as a benchmark.

Then from the results of examination of FF5F Model on CNAS stock market, we conclude that the profitability and investment factors have limited additional explanatory power, and Fama-French Five-Factor Model does not have significant improvement in explaining average excess stock returns comparing with the original three-factor model on CNAS stock market, which is inconsistent with the findings on U.S. stock market. Similarly, if investors want to invest in Chinese stock market, it’s better and easier to select the portfolios that constructed based on FF3F instead of FF5F Model. However, if investors invest on U.S. stock market, it is wiser to choose their portfolios that constructed based on FF5F Model, since FF5F Model performs better than FF3F Model on U.S. stock market.

In addition, our attempts to find the economic explanation of FF factors on Chinese stock market suggest that FF factors don’t lose their explanatory power in the presence of the innovations of selected state variables in both time-series and CSRs on CNAS stock market over the research period, and the presence of innovations of state variables do capture more variation of average returns than original FF3F Model. The findings indicate that on Chinese stock market, constructing portfolios tilt towards the innovations of the four economic variables cannot gain extra risk premium in addition to the FF factors. FF3F Model seems to be the best choice in practice so far on Chinese stock market.

Finally, our findings in the last chapter suggest that FF factors are not proxy of distress risk on CNAS stock market, instead, the distress risk factor explains the time-series excess average stock returns combining with FF three factors. The augmented four-factor model explains the time-series variation of average excess stock returns slightly better than FF3F Model on CNAS stock market. In this case, for example, if constructing portfolios tilt towards our mimicking distress risk factor in addition to FF factors, one can expect more average returns than constructing portfolios only based on the original FF factors. However, the extra benefit comes from distress risk factor is limited. Moreover, for instance, our findings are also can be implemented by companies to estimate the cost of equity; by investors to evaluate the inherent value of equities and to make their decisions.

All in all, in order to keep up with the pace of China's reforms and the globalization of its economy, the Chinese stock market has experienced fast development and overall institutional reforms. Considering the special features, the asset returns and its determinants might be different between Chinese stock market and those of developed stock markets such as U.S. and European markets. Our present research fails to find the economic explanation for the success of FF factors on CNAS stock market, therefore, we propose to consider the risk factors which feature the special characteristics of the Chinese stock market or other economic variables that related to stock returns in further researches.

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Appendix A

Errors-in-Variables (EIV) problem and Shanken correction procedure

In applying standard OLS method to a CSR, we assume that the right-hand variables β are fixed. However, when implementing Fama-MacBeth two-stage approach, the β in the CSR are not fixed, of course, but are estimated in the TSR. Therefore, the explanatory variable in the CSR is measured with error. Hence, it is very important to determine whether the relation between average stock returns and the risk factors is the result of the misspecification of the asset pricing model or is simply a consequence of the EIV problem.

Shanken (1992) modifies the traditional two-pass procedure and derives an asymptotic distribution of the CSR estimator within a multifactor framework in which asset returns are generated by portfolio returns and prespecified factors. Shanken also provides an adjustment for the standard errors of the CSR estimators with a multifactor interpretation

Cochrane (2005) derives the correct asymptotic standard errors due to Shanken (1992),. With the simplifying assumption that the errors ε are i.i.d. over time and independent of the factors, the result is

$$\sigma^2\left(\hat{\lambda}\right)=\frac{1}{T}\left[\left(\beta'\beta\right)^{-1}\beta'\Sigma\ \beta\left(\beta'\beta\right)^{-1}\left(1+\lambda'\Sigma_f^{-1}\lambda\right)+\Sigma_f\right] \tag{A.1}$$

where λ is the factor risk premia, β is the TSR coefficients matrix, Σ is the variance-covariance matrix of residuals, Σ_f is the variance-covariance matrix of the factors.

Appendix B

Performance of FF3F Model and FF5F Model on U.S. stock market

Table B.1 Time-series regression of six value-weighted Size-B/M portfolios on U.S. stock market (period: July 2004- May 2015, 131 months)

The time-series regression results of six value-weighted Size-B/M portfolios on FF3F Model are displayed in this table. Across the columns are the two size groups (Small and Big) and across the rows are the three B/M ratio groups (Low, Medium and High). The left part of the table reports the coefficients obtained from the time-series regressions and adjusted R-square. Correspondingly, the right part of the table is t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator, and the standard error of the estimation. Numbers in bold are the t-statistics which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

	Book-to-Price (B/P) ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
S	-0.1217	0.1085	0.0093	-1.7229	**2.4742**	0.2413
B	0.0851	-0.0443	-0.0444	**2.1144**	-0.6264	-0.5223
		b			*t* (*b*)	
S	1.0754	0.9785	0.9863	**41.1094**	**69.4224**	**84.3440**
B	0.9633	1.0243	1.0523	**58.2424**	**40.0675**	**38.0928**
		s			*t* (*s*)	
S	1.0115	0.8834	0.8824	**24.8082**	**38.7934**	**54.5879**
B	-0.1132	-0.1264	0.0162	**-4.5531**	**-2.8759**	0.3696
		h			*t* (*h*)	
S	-0.2140	0.2183	0.6748	**-4.5584**	**8.0641**	**30.4628**
B	-0.2679	0.1040	0.8434	**-11.5717**	**2.2594**	**12.6276**
		Adj. R-square			Residual standard error	
S	0.9781	0.9894	0.9945	0.0086	0.0057	0.0045
B	0.9852	0.9691	0.9683	0.0047	0.0078	0.0100

Table B.2 Time-series regressions of 25 value-weighted Size-B/M portfolios on FF3F Model, U.S. stock market (July 2004- May 2015; 131 months)

This table presents the time-series regressions results of 25 value-weighted Size-B/M portfolios on FF3F Model, Across the columns are five size groups and across the rows are five B/M groups. The left part of the table is the coefficients of the regressions and adjusted R-square. Correspondingly, the right part of the table is t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator, and the standard error of the residuals. Numbers in bold are the t-statistics which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			a					*t* (*a*)		
S	-0.6227	-0.0461	-0.2137	-0.0201	0.0095	**-3.8594**	-0.3958	**-2.2758**	-0.1898	0.0700
2	-0.0157	0.1969	0.2419	0.0694	-0.1141	-0.1646	**2.0533**	**2.4736**	0.5674	-1.1176
3	-0.0001	0.2748	0.2386	0.2086	0.1795	-0.0012	**2.3832**	**2.0916**	1.7311	1.1510
4	0.2159	0.1115	-0.2138	0.1989	-0.0792	1.9938	1.0221	-1.1539	1.7058	-0.4470
B	0.0118	0.1418	0.1174	-0.4563	0.0876	0.1585	1.8226	1.2430	**-2.1494**	0.3999
			b					*t* (*b*)		
S	1.1111	0.9998	0.9807	0.8738	0.9491	**21.3603**	**26.4149**	**40.2759**	**18.7566**	**23.2255**
2	1.0783	0.9970	0.9603	0.9170	1.0880	**30.6065**	**34.4155**	**35.9649**	**38.7462**	**32.5759**
3	1.1181	1.0611	1.0178	1.0175	0.9960	**24.4732**	**38.8964**	**28.8771**	**31.6152**	**25.8979**
4	1.0636	1.0948	1.1823	1.0606	1.0737	**23.9754**	**25.6645**	**15.7197**	**18.5949**	**22.3479**
B	0.9766	0.9204	0.9536	1.1195	1.0956	**32.9666**	**51.0610**	**26.0271**	**12.5321**	**13.9923**
			s					*t* (*s*)		
S	1.2024	1.1139	0.9662	0.9804	0.9628	**15.0696**	**19.5260**	**18.0505**	**24.1812**	**15.0989**
2	1.0246	1.0148	0.9695	0.8377	0.8737	**14.0170**	**30.4977**	**20.2644**	**24.1121**	**13.6579**
3	0.7051	0.6803	0.6301	0.5290	0.6720	**12.6354**	**13.1719**	**13.3856**	**8.0100**	**10.1764**
4	0.4484	0.3314	0.3331	0.2586	0.2551	**10.0698**	**5.9816**	**4.1488**	**3.6079**	**3.6529**
B	-0.1985	-0.1845	-0.1960	-0.3180	0.0284	**-4.6713**	**-5.0276**	**-3.5593**	**-3.8461**	0.2377

Table B.2 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
			h					*t* (*h*)		
S	-0.1231	0.0783	0.2095	0.4896	0.7294	-1.9032	1.5451	**4.3873**	**6.2762**	**15.9565**
2	-0.2822	-0.0499	0.2415	0.4500	0.8687	**-3.5719**	-0.9898	**7.2889**	**11.6221**	**14.8860**
3	-0.3366	-0.0488	0.0939	0.2361	0.6287	**-8.7449**	-0.8861	**2.3422**	**3.7369**	**7.6054**
4	-0.3117	-0.1128	-0.0435	0.2368	0.6970	**-7.4663**	-1.7359	-0.3747	**2.4142**	**6.8010**
B	-0.3729	0.0392	0.1710	0.5757	0.8925	**-9.0766**	1.0111	**3.6067**	**7.2239**	**7.8523**
			Adj R-square					Residual standard error		
S	0.9122	0.9398	0.9606	0.955	0.9655	0.0194	0.0147	0.0113	0.0119	0.0115
2	0.9454	0.9602	0.9655	0.9589	0.9653	0.0138	0.0113	0.0105	0.0112	0.0127
3	0.9452	0.9500	0.9457	0.9283	0.9114	0.0130	0.0121	0.0124	0.0143	0.0178
4	0.9460	0.9397	0.9196	0.9102	0.9231	0.0116	0.0125	0.0158	0.0157	0.0163
B	0.9595	0.9429	0.9248	0.9155	0.8728	0.0078	0.0094	0.0116	0.0157	0.0222

Table B.3 Cross-sectional regressions on FF3F Model of six Size-B/M portfolios and 25 Size-B/M portfolios, U.S. stock market (July 2004- May 2015)

This table presents the results of cross-section regressions on FF3F Model of FF six value-weighted Size-B/M portfolios (Panel A) and 25 value-weighted Size-B/M portfolios (Panel B). In each panel, the first row is the cross-sectional regressions' coefficients (coef.); the second row is the corresponding Fama-MacBeth t-statistics (FM t-stats) at 5% confidence level, and the third row is the Shanken corrected t-statistics (SH t-stats). The numbers in bold are the t-stats which are significant at 5% level. The adjusted R-squares are percentage values.

Regression: $R_{i,t} - R_f = \alpha_i + \gamma_M \hat{b}_i + \gamma_{SMB} \hat{s}_i + \gamma_{HML} \hat{h}_i + \varepsilon_{i,t}$

	α	γ_M	γ_{SMB}	γ_{HML}	Adj. R^2 (%)
Panel A: Cross-sectional regression of six Size-B/M portfolios					
gamma (coef.)	0.0185	-0.0117	0.0012	0.0002	58.14
FM t-stats	(**2.0663**)	(-1.2023)	(0.6239)	(0.1026)	
SH t-stats		(**-3.1339**)	(0.6235)	(0.1025)	
Panel B: Cross-sectional regression of 25 Size-B/M portfolios					
gamma (coef.)	0.0132	-0.5547	0.0561	-0.0730	40.76
FM t-stats	(**3.0609**)	(-0.9691)	(0.2817)	(-0.3246)	
SH t-stats		(-1.4809)	(0.2813)	(-0.3232)	

Table B.4 Time-series regressions of six value-weighted Size-B/M portfolios, Size-OP portfolios and Size-Inv portfolios on FF5F Model on U.S. stock market (July 2010 to May 2015, 59 months)

This table presents the time-series regressions results of FF5F model. In each panel, the regression intercept a, the regression coefficients b, s, h, r and c of market factor, size factor, value factor, profitability factor and investment factor, adjusted R square are respectively presented in the left part of the table, the corresponding t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator and residual standard error are presented in the right part. Panel A is the regressions on six Size-B/M portfolios, across the columns are the two size groups (Small and Big) and across the rows are the three B/M groups (Low, Medium, and High). Panel B is the regression results of six Size-OP portfolios, same as Panel A, across the columns are the two size groups and across the rows are the three OP groups (Weak, Neutral and Robust). Panel C is the regression results of six Size-Inv portfolios, across the columns are the two size groups and across the rows are the three Investment groups (Aggressive, Neutral and Conservative). Numbers in bold are the t-stats which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{i,t}$

Panel A: Time-series regressions on six Size-B/M portfolios

	Book-to-Market (B/M) ratio					
	L	M	H	L	M	H
		a			$t(a)$	
S	-0.2123	-0.0328	0.2391	-1.2440	-0.3040	1.4394
B	0.0339	-0.0369	0.0197	0.2766	-0.2794	0.1673
		b			$t(b)$	
S	0.9867	1.0036	0.8091	**18.0426**	**37.3893**	**18.0305**
B	1.0715	1.1142	1.0577	**30.4708**	**21.6453**	**42.6438**
		s			$t(s)$	
S	0.7036	0.7975	0.4312	**13.4733**	**17.5148**	**5.5548**
B	0.2231	0.1980	0.1550	**4.6577**	**3.4748**	**2.2473**
		h			$t(h)$	
S	-0.2137	0.2549	0.3912	**-2.0573**	**4.1878**	**3.8325**
B	-0.2152	0.0582	0.6456	**-4.9748**	0.9063	**9.2306**
		r			$t(r)$	
S	-0.7327	-0.1351	-0.3846	**-5.4871**	**-2.2599**	**-3.0270**
B	-0.1506	-0.0322	0.0110	**-2.7377**	-0.3318	0.1531
		c			$t(c)$	
S	-0.3047	-0.2155	-0.0974	**-2.7655**	**-2.3334**	-0.7657
B	-0.2294	-0.0887	-0.1666	**-2.3567**	-1.1923	-1.4554
		Adj. R-square			Residual standard error	
S	0.9517	0.9733	0.9084	0.0115	0.0080	0.0125
B	0.9670	0.9591	0.9580	0.0077	0.0088	0.0089

Table B.4 Continued

Panel B: Time-series regressions on Size-OP portfolios						
	Operating Profitability					
	W	N	R	W	N	R
		a			*t* (*a*)	
S	-0.0188	0.0898	-0.0396	-0.3438	1.1708	-0.4349
B	-0.0842	0.0989	-0.0640	-0.7461	2.2880	-1.9871
		b			*t* (*b*)	
S	0.9812	0.9853	1.0646	**81.0285**	**51.1117**	**32.7726**
B	1.1136	0.9412	1.0298	**27.2225**	**50.5000**	**97.2971**
		s			*t* (*s*)	
S	0.8675	0.9675	0.9317	**33.4687**	**20.9395**	**14.3934**
B	-0.0693	-0.0541	-0.1339	-1.0857	-1.2950	**-4.5316**
		h			*t* (*h*)	
S	-0.1143	0.2669	0.2011	**-4.5007**	**6.3486**	**3.9980**
B	0.2443	0.0392	-0.0708	**4.5818**	1.0984	**-2.7060**
		r			*t* (*r*)	
S	-0.6348	0.2597	0.4475	**-18.4610**	**5.1374**	**9.5450**
B	-0.5864	-0.1016	0.3304	**-8.4796**	**-2.7847**	**12.2607**
		c			*t* (*c*)	
S	0.0768	-0.0627	-0.1247	1.6662	-1.0611	-1.5351
B	-0.2849	0.1389	-0.0839	**-3.0221**	**2.6995**	**-2.0856**
		Adj. R-square			Residual standard error	
S	0.9945	0.9851	0.9826	0.0040	0.0058	0.0063
B	0.9775	0.9863	0.9903	0.0069	0.0041	0.0033

Panel C: Time-series regressions on Size-Inv portfolios						
	Investment					
	A	N	C	A	N	C
		a			*t* (*a*)	
S	0.0071	0.1144	-0.0540	0.1573	**2.3620**	-0.8730
B	0.0259	-0.0428	0.0831	0.4733	-0.7299	1.1236
		b			t (*b*)	
S	0.9681	0.9710	1.0880	**47.1125**	**35.9423**	**81.6853**
B	1.0521	0.9912	0.9326	**77.8118**	**48.6599**	**32.4959**
		s			*t* (*s*)	
S	0.9702	0.8942	0.8760	**30.5318**	**26.8312**	**19.7427**
B	-0.1786	-0.0167	-0.0835	**-5.7904**	-0.9118	**-2.1632**

Table B.4 Continued

Panel C: Time-series regressions on Size-Inv portfolios						
	Investment					
	A	N	C	A	N	C
		h			*t* (*h*)	
S	0.0238	0.1754	-0.0163	0.7234	**5.4018**	-0.3663
B	-0.0658	0.0615	-0.0260	-1.4661	1.3401	-0.4450
		r			*t* (*r*)	
S	-0.2181	0.1339	-0.2339	**-4.7274**	**3.5684**	**-5.6108**
B	-0.0174	0.0573	-0.0001	-0.3659	1.1884	-0.0013
		c			*t* (*c*)	
S	-0.4264	0.1159	0.3567	**-7.7210**	**2.0770**	**5.2777**
B	-0.5734	0.1819	0.6429	**-8.1165**	**3.4479**	**7.3145**
		Adj. R-square			Residual standard error	
S	0.9907	0.9879	0.9908	0.0048	0.0051	0.0051
B	0.9799	0.9872	0.9764	0.0052	0.0041	0.0054

Appendix C

Time-series regression of six Size-B/P portfolios, six Size-OP portfolios and six Size-Inv portfolios on FF3F Model (Chinese stock market)

Table C.1 Time-series regression of three sets of portfolios on FF3F Model, Chinese A-share stock market (July 2010- May 2015, 59 months)

This table presents the time-series regressions results of six Size-B/P portfolios, six Size-OP portfolios and six Size-Inv portfolios on FF3F Model on Chinese stock market in Panel A, Panel B, and Panel C respectively. In each panel, the regression coefficients and adjusted R-square are presented in the left part of the table, the corresponding t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator and residual standard error are presented in the right part. Across the columns of each panel are the two size groups (S and B); across the rows of Panel A are the three B/M groups (L, M and H)., across the rows of Panel B are the three OP groups (W, N and R), across the rows of Panel C are the three Investment groups (A, N and C). Numbers in bold are the t-stats which are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

Panel A: Time-series regression of six value-weighted Size-B/P portfolios						
Size	Book-to-Price (B/P) ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
S	0.0113	0.0113	0.0112	**7.4842**	**4.5837**	**6.1412**
B	0.0123	0.0092	0.0123	**6.2322**	**3.3146**	**6.4849**
		b			*t* (*b*)	
S	0.8979	0.9231	0.9059	**32.6701**	**27.0157**	**32.2014**
B	0.8504	1.0340	0.8424	**27.3918**	**22.4104**	**22.1472**
		s			*t* (*s*)	
S	0.9057	0.8874	0.8548	**27.9738**	**15.5660**	**19.8422**
B	-0.1441	-0.1149	-0.0931	**-3.4693**	-1.3686	**-2.7201**
		h			*t* (*h*)	
S	-0.4025	-0.3497	-0.0262	**-5.0751**	**-4.3756**	-0.4383
B	-0.9630	-0.4761	0.6607	**-15.1937**	**-5.5671**	**7.1594**
		Adj. R-square			Residual standard error	
S	0.9803	0.9782	0.9746	0.0114	0.0120	0.0119
B	0.9623	0.9545	0.9542	0.0122	0.0147	0.0130

Table C.1 Continued

Panel B: Time-series regression of six value-weighted Size-OP portfolios						
	Profitability					
	W	N	R	W	N	R
		a			*t* (*a*)	
S	0.0038	0.0042	-0.0022	1.3466	0.7791	-0.5303
B	0.0000	0.0027	0.0010	-0.0179	1.5449	0.3059
		b			*t* (*b*)	
S	0.9236	0.9733	1.0657	**24.3001**	**17.2826**	**17.4507**
B	1.0967	0.9896	1.1164	**19.0453**	**34.3179**	**20.3752**
		s			*t* (*s*)	
S	1.0674	0.8611	0.7540	**7.9772**	**5.1362**	**5.5995**
B	0.4230	0.3508	-0.1688	**3.8493**	**7.9956**	-1.5525
		h			*t* (*h*)	
S	-0.2302	-0.5825	-0.4059	-1.8362	**-3.4193**	**-2.2086**
B	-0.1523	-0.4188	-0.7060	-1.3302	**-4.9840**	**-6.5449**
		Adj. R-square			Residual standard error	
S	0.9456	0.9158	0.8514	0.0200	0.0261	0.0356
B	0.9520	0.9698	0.9388	0.0174	0.0127	0.0188

Panel C: Time-series regressions of six value-weighted Size-Inv portfolios						
	Investment					
	A	N	C	A	N	C
		a			*t* (*a*)	
S	-0.0015	0.0024	-0.0002	-0.7269	1.1784	-0.1061
B	-0.0038	0.0000	-0.0025	**-2.4503**	0.0310	-1.3087
		b			*t* (*b*)	
S	0.9667	0.9745	0.9521	**50.2415**	**37.7947**	**34.0437**
B	1.0323	1.0393	1.0796	**31.6716**	**37.0603**	**26.3027**
		s			*t* (*s*)	
S	1.0170	0.9787	1.1180	**16.8657**	**22.2040**	**19.8524**
B	0.3535	0.3491	0.5370	**5.0630**	**7.1627**	**8.8230**
		h			*t* (*h*)	
S	-0.3873	-0.4312	-0.2089	**-3.2013**	**-5.7192**	**-2.3319**
B	-0.6595	-0.3505	-0.1090	**-7.1360**	**-4.6239**	-0.9868
		Adj. R-square			Residual standard error	
S	0.9508	0.9778	0.9701	0.0197	0.0131	0.0151
B	0.9621	0.9742	0.9595	0.0155	0.0121	0.0160

Appendix D

Time-series regressions on single innovation of selected state variables in addition to excess market return

Table D.1 Time-series regressions on single innovation of state variables (December 2006- May 2015)

This table presents the four time-series regressions on the single innovation of state variables in addition to excess market return, only loadings on the innovations are reported. The left-hand part of the table presents the loadings and right-hand part is the corresponding t-statistics corrected for heteroscedasticity and autocorrelation using the Newey-West estimator. Across the columns of each part are the five size quintiles and across the rows are five B/P ratio quintiles. Numbers in bold indicate statistical significance at 5% confidence level.

Regressions:

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDIV} IDIV + \nu_{i,t}$$
$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,ITERM} ITERM + \nu_{i,t}$$
$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IDEF} IDEF + \nu_{i,t}$$
$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{M,t} - R_f) + \beta_{i,IRF} IRF + \nu_{i,t}$$

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
	Panel A: Regressions on market factor and IDIV									
	β_{IDIV}					$t(\beta_{IDIV})$				
S	-19.4121	-23.4954	-21.6904	-20.6291	-20.2875	**-2.4626**	**-2.9855**	**-3.3198**	**-2.7667**	**-2.5375**
2	-24.2059	-18.1294	-21.2079	-24.0719	-22.1941	**-3.5465**	**-2.5009**	**-3.1129**	**-3.3345**	**-3.0771**
3	-19.6072	-25.9214	-17.4444	-20.3365	-20.8928	**-2.8355**	**-3.7192**	**-3.1053**	**-3.8017**	**-3.6844**
4	-16.2248	-17.2302	-16.4696	-17.8200	-20.6227	**-2.6344**	**-2.8928**	**-3.3502**	**-3.2671**	**-4.5735**
B	-9.5801	-7.8102	-12.3718	-8.8154	-13.2603	-1.7570	-1.8305	**-3.1659**	**-2.1580**	**-2.4231**

Table D.1 Continued

Size	B/P ratio									
	L	2	3	4	H	L	2	3	4	H
Panel B: Regressions on market factor and ITERM										
	β_{ITERM}					$t(\beta_{ITERM})$				
S	2.1979	3.1786	2.8511	1.3541	1.2907	0.4802	0.7913	0.7025	0.3304	0.3179
2	4.3519	3.1261	4.1306	2.5430	0.8026	1.2628	0.9301	1.0870	0.7630	0.2458
3	3.9247	4.4774	2.6859	1.3648	-0.1431	0.9611	1.3439	0.8586	0.4922	-0.0510
4	3.9734	4.1571	2.4330	0.9741	-1.4101	1.3249	1.4546	1.0761	0.4080	-0.6578
B	3.2004	2.5767	0.1241	-0.3270	-4.0864	1.4070	1.6004	0.0775	-0.2406	-1.6547
Panel C: Regressions on market factor and IDEF										
	β_{IDEF}					$t(\beta_{IDEF})$				
S	3.7428	1.5203	2.8085	3.6790	2.4471	0.5640	0.2210	0.4635	0.6228	0.4097
2	1.1381	0.2448	1.4571	3.7144	2.0826	0.1970	0.0427	0.2412	0.6908	0.4492
3	4.1031	1.5287	1.4575	1.5554	2.0615	0.6695	0.2649	0.2756	0.3260	0.5193
4	-0.0922	-0.1408	0.8468	-0.2386	3.9225	-0.0184	-0.0270	0.2104	-0.0533	1.2321
B	3.6214	-0.1257	1.9757	-0.8604	2.0447	0.8670	-0.0392	0.7604	-0.3124	0.5102
Panel D: Regressions on market factor and IRF										
	β_{IRF}					$t(\beta_{IRF})$				
S	-6.1567	-5.3639	-6.3742	-4.2995	-3.4335	-1.9355	-1.5769	**-2.0364**	-1.2874	-1.1219
2	-7.6940	-4.5895	-6.7521	-5.6511	-3.2150	**-2.6154**	-1.3826	**-2.3392**	**-2.0012**	-1.3050
3	-6.5573	-5.9295	-5.8271	-3.8025	-3.0693	**-2.0189**	**-2.1871**	**-2.2262**	-1.6033	-1.4693
4	-6.3293	-6.0462	-4.1635	-2.2150	-0.8936	**-2.6779**	**-2.6614**	**-2.0668**	-0.9592	-0.4960
B	-4.3878	-2.0402	0.1862	0.1231	1.3394	**-2.1198**	-1.2005	0.1158	0.0756	0.6946

Appendix E

Derivation process of Merton's default probability and distance-to-default

The default probability is the probability that the firm's assets value is less than the book value of the firm's liabilities, which is:

$$P_t = Prob\left(V_{A,t+T} \le X_t \middle| V_{A,t}\right) = Prob\left(ln\left(V_{A,t+T}\right) \le ln\left(X_t\right) \middle| V_{A,t}\right)$$

where P_t is the probability of default at time *t*, $V_{A,t}$ and X_t are the market value of the firm's assets and the book value of the firm's liabilities at time *t*, and $V_{A,t+T}$ is the market value of the firm's assets due at time *T*.

Since the value of firm's assets follows GBM of $dV_A = \mu V_A dt + \sigma_A V_A dW$ (equation 3.5), the value of assets at time *t* is given by:

$$ln\left(V_{A,t+T}\right) = ln\left(V_{A,t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A \sqrt{T}\varepsilon_{t+T}$$

where $\varepsilon_{t+T} = \frac{W\left(t+T\right) - W\left(t\right)}{\sqrt{T}}$, $\varepsilon_{t+T} \sim N\left(0,1\right)$, μ is the drift rate which is the expected return on the firm's asset, and ε is the random component of the firm's return which is normally distributed assumed by BS model.

Then the probability of default above can be rewritten as follows:

$$P_t = Prob\left(ln\left(V_{A,t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A \sqrt{T}\varepsilon_{t+T} \le ln\left(X_t\right)\right)$$

$$= Prob\left(-\frac{ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \ge \varepsilon_{t+T}\right)$$

According to the normal distribution of ε, the probability of default P_t can be defined in terms of the cumulative normal distribution:

$$P_t = N\left(-\frac{ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \right)$$

which is the Merton's probability of default.

Appendix F

Time-series and cross-sectional regressions of 18 Size-B/P-DR sorted portfolios on FF3F model

Table F.1 Time-series regressions of 18 Size-B/P-O-score sorted portfolios on FF3F Model, Chinese stock market (July 2005 to May 2015)

This table reports the time-series regression results for 18 Size-B/P ratio-O-score on FF3F Model. The stocks are divided into two size groups, three B/P groups, and three groups based on their O-score, seperately. The intersection of these groups forms 18 portfolios. The left part of the table is the coefficients of time-series regressions and adjusted R-square, the right part is the corresponding t-stats corrected for heteroscedasticity and autocorrelation using Newey-West estimator and residual standard error, and the numbers in bold are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

Small size						
O-score	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
O1	0.0003	-0.0015	-0.0042	0.0950	-0.6211	-1.4931
O2	-0.0072	-0.0019	-0.0019	**-2.0880**	-0.8494	-0.6544
O3	-0.0056	-0.0011	0.0000	-1.8313	-0.3788	-0.0104
		b			*t* (*b*)	
O1	0.9738	0.9995	0.9741	**18.6385**	**19.9970**	**21.0746**
O2	1.0262	0.9931	1.0063	**18.9585**	**23.7498**	**17.0678**
O3	0.9945	0.9981	0.9964	**18.7994**	**18.4143**	**16.3521**
		s			*t* (*s*)	
O1	1.3451	1.3748	1.5414	**11.4333**	**12.7305**	**14.9231**
O2	1.4930	1.3699	1.3850	**13.5019**	**15.0567**	**11.7254**
O3	1.5798	1.4035	1.3333	**15.4323**	**12.6156**	**11.2084**
		h			*t* (*h*)	
O1	-0.1961	0.1113	0.5427	-1.3753	0.8522	**3.9638**
O2	0.0477	0.1810	0.4657	0.3208	1.4722	**3.4695**
O3	0.1713	0.3048	0.4942	1.2575	**2.3177**	**3.4456**
		Adj R-square			Residual standard error	
O1	0.8677	0.9121	0.9038	0.0404	0.0329	0.0355
O2	0.9000	0.9179	0.9031	0.0368	0.0315	0.0353
O3	0.9072	0.9058	0.8986	0.0352	0.0344	0.0356

Table F.1 Continued

Big size						
O-score	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
O1	-0.0017	-0.0029	-0.0046	-0.7289	-1.0484	-1.7760
O2	-0.0036	-0.0005	-0.0048	-1.2359	-0.1598	-1.8854
O3	-0.0060	-0.0063	-0.0007	-1.8987	**-2.1111**	-0.2422
		b			*t* (*b*)	
O1	0.9549	1.0330	1.0255	**18.6257**	**20.9052**	**18.9205**
O2	1.0119	1.0910	1.0489	**18.3348**	**19.0292**	**16.7194**
O3	1.0332	1.1153	1.0781	**15.0781**	**16.2983**	**22.2291**
		s			*t* (*s*)	
O1	0.4950	0.7539	0.8142	**5.1068**	**6.2125**	**8.9078**
O2	0.7978	0.6842	0.7971	**7.4561**	**6.0882**	**7.4711**
O3	0.8567	0.8561	0.7651	**7.0660**	**6.7420**	**7.2620**
		h			*t* (*h*)	
O1	-0.6448	-0.0470	0.4973	**-5.0173**	-0.3281	**4.4956**
O2	-0.3376	0.0427	0.6607	**-2.3818**	0.3042	**4.6627**
O3	-0.2528	0.1370	0.8074	-1.6469	0.9250	**6.4202**
		Adj R-square			Residual standard error	
O1	0.8678	0.8800	0.9066	0.0345	0.0361	0.0323
O2	0.8750	0.8936	0.9081	0.0364	0.0353	0.0331
O3	0.8542	0.8781	0.9109	0.0409	0.0398	0.0337

Table F.2 Time-series regressions of 18 Size-B/P-DLI sorted portfolios on FF3F Model, Chinese stock market (July 2005 to May 2015)

This table reports the time-series regression results of 18 Size-B/P-DLI sorted portfolios on FF3F Model. The stocks are divided into two size groups based on the breakpoint of median market capitalization, and the breakpoints for the three B/P groups are the top 30%, median 40% and bottom 30% of B/P ratio, similarly as B/P groups, the stocks are divided into three groups based on their O-score (O1, O2 and O3, represent the low, medium and high O-score separately). The intersection of two size groups, three B/P groups and O-score groups form 18 portfolios. The left part of the table is the coefficients of time-series regressions and adjusted R-square, the right part is the corresponding t-stats corrected for heteroscedasticity and autocorrelation using Newey-West estimator and residual standard error, and the numbers in bold are significant at 5% confidence level.

Regression: $R_{i,t} - R_f = a_i + b_i(R_{M,t} - R_f) + s_i SMB + h_i HML + e_{i,t}$

Small size						
DLI	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
D1	-0.0025	0.0002	-0.0031	-0.9101	0.0587	-0.9167
D2	-0.0081	-0.0019	-0.0005	**-2.8124**	-0.8704	-0.2072
D3	0.0014	0.0004	-0.0013	0.3786	0.1655	-0.5089
		b			*t* (*b*)	
D1	0.9817	0.9758	0.9545	**19.5959**	**21.2488**	**23.9619**
D2	1.0116	1.0041	1.0103	**20.3742**	**22.2973**	**20.1025**
D3	1.0067	1.0209	1.0050	**19.4264**	**25.5842**	**16.4963**
		s			*t* (*s*)	
D1	1.4510	1.4549	1.6158	**17.1267**	**12.7620**	**13.5801**
D2	1.6063	1.4122	1.4775	**14.7615**	**16.0700**	**12.1172**
D3	1.4346	1.3751	1.3206	**14.0215**	**14.3170**	**12.4977**
		h			*t* (*h*)	
D1	-0.2634	-0.1172	0.4312	-1.9823	-0.8851	**2.8019**
D2	-0.0145	0.0316	0.3284	-0.1077	0.2800	**2.3027**
D3	0.1395	0.2050	0.4360	1.0807	1.7397	**3.3278**
		Adj R-square			Residual standard error	
D1	0.9173	0.9073	0.8990	0.0321	0.0339	0.0364
D2	0.9211	0.9286	0.9087	0.0328	0.0297	0.0347
D3	0.8847	0.9205	0.9090	0.0389	0.0317	0.0336

Table F.2 Continued

Big size						
DLI	B/P ratio					
	L	M	H	L	M	H
		a			*t* (*a*)	
D1	-0.0001	-0.0032	-0.0051	-0.0287	-1.2382	-1.6917
D2	-0.0054	-0.0022	-0.0022	-1.9525	-0.8175	-0.8457
D3	-0.0027	-0.0051	-0.0039	-0.8710	-1.6936	-1.6293
		b			*t* (*b*)	
D1	0.9290	1.0053	0.9359	**20.0667**	**27.0452**	**17.9607**
D2	1.0405	1.0926	1.0638	**15.5261**	**20.9450**	**20.9343**
D3	1.0942	1.1301	1.0846	**22.2336**	**17.9663**	**18.8849**
		s			*t* (*s*)	
D1	0.6290	0.8346	0.9219	**5.9958**	**7.5760**	**8.1997**
D2	0.7953	0.7991	0.7913	**6.3616**	**7.6778**	**8.4618**
D3	0.6881	0.7427	0.7786	**6.7352**	**5.4622**	**7.5786**
		h			*t* (*h*)	
D1	-0.6961	-0.2435	0.4531	**-5.5203**	-1.6542	**3.5546**
D2	-0.4687	-0.1322	0.4000	**-3.2566**	-0.8330	**3.3928**
D3	-0.2559	0.0840	0.7448	-1.7169	0.6183	**5.6516**
		Adj R-square			Residual standard error	
D1	0.8559	0.8798	0.8687	0.0362	0.0356	0.0366
D2	0.8724	0.8993	0.9105	0.0379	0.0346	0.0323
D3	0.8781	0.8830	0.9203	0.0380	0.0387	0.0317

Appendix G

List of publications and conferences

Journal

Jiao, W., and Lilti, J.J. (2017), Whether profitability and investment factors have additional explanatory power comparing with Fama-French Three-Factor Model: empirical evidence on Chinese A-share stock market. China Finance and Economic Review, 5(1), 7.

Conference

Jiao,W., and Zhang, J. (2016), Do the innovations of predictive variables explain Chinese stock market? The 13th Edition of Augustin Cournot Doctoral Days (ACDD), April 21st and 22nd of 2016, Strasbourg, France.

Jiao, W., and Lilti, J.J. (2017), Exploring Fama-French Five-Factor Model on Chinese A-share stock market. The 34th International Conference of the French Finance Association, May 31st, June 1st and 2nd of 2017, Valence, France.