Conditional correlations and investment shocks: Evidence from the Chinese sectors

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Abstract

This chapter aims to advance the understanding of the relationship between sectors' heterogeneity in the form of different sensitivities to investment-specific shocks and the conditional correlations of sector portfolios. For this purpose, we examined the dynamic conditional correlations between the 12 Chinese sector returns and the market equity index focusing on the 2008-2009 global financial crisis and the 2010-2011 European debt crisis. Using a sample of the 12 Chinese sector-level indices, we found that the conditional correlations vary significantly across sectors and crises. To impose economic interpretations on the finding, we associated the magnitude difference of the conditional correlations among sectors with different sensitivities to industry-specific shocks within the general equilibrium model, as in Papanikolaou (2011). This paper further investigated the determinants of the sector-level correlations by conducting a battery of panel regression analyses. Our main finding is that crisis dummies and investment-specific proxies for investment or growth opportunities – such as book-to-market, capital expenditure, leverage (long-term debt ratio), growth rate of industry size, and Tobin's Q – are significantly associated with the magnitude of conditional correlations.

JEL classification: G12, G15, C32

Keywords: Conditional correlation; Investment-specific shock; Growth opportunity; Financial crisis

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1 Introduction

1.1 Introduction

Stock returns tend to comove. Individual, industry, and market returns comove at different degrees. To investigate dynamic relationship among financial assets, measuring the degree of comovement is critical dueto many financial fields of studies, including asset allocation, risk management, pricing and hedging. Surprisingly, only few systematic academic papers both in finance and in economics address what determinants drive different degrees of comovement. Our paper is motivated by this empirical gap. Ultimately, we aim to advance our understanding of the relationship between sectors' heterogeneity in the form of different sensitivities to industry-specific shocks and the conditional correlations of sector portfolios.

As starters, we need to decide which level of portfolios is appropriate for the analysis. A key piece of the puzzle is that firms with similar characteristics comove with each other and a key element to complete the puzzle is that exposure to the same common risk factor accounts for a substantial fraction of comovement among all characteristic-sorted portfolios. Along with this line, industry portfolio returns are likely to be as a natural ingredient for a study of what drives comovements since they are in similar business lines. However, industry-level analysis has received limited academic attention in finance despite its practical popularity. [1] One reason for this gap is that standard asset pricing models limitedly explain industry-related patterns. For example, Fama & French (1997) found that the traditional CAPM or three-factor asset pricing model produces a poor estimates for the industry cost of equity. Lewellen, Nagel & Shanken (2010) showed that several risk-based asset pricing models are rejected because common test statistics for the models is not informative about its true performance, and thus fail to explain the cross-section of returns on industry portfolios.

Recent papers that studied various dimensions of industry portfolio patterns produced some inspiring empirical findings. For example, Kalotychou, Staikouras & Zhao (2014) showed that the predictability of conditional correlation models describing empirical regularities leads to signicant investment performance gains using sector returns. Hou & Robinson (2006) provided the evidence that firms in concentrated industries earn lower

[1] There is ample evidence that industries exhibit heterogeneous patterns. For example,Petersen & Strongin (1996) examined why some industries are more cyclical than others. They found that durable-goods industries are three times more cyclical than non-durable goods industries and that within durable-goods industries, the proportion of variable and fixed factor inputs, market concentration, and labor hoarding are important determinants of cyclical behavior.

returns after controlling for size, BM, and momentum. Moskowitz & Grinblatt (1999) showed that individual stock momentum is largely driven by industry momentum and that stocks within an industry tend to be more correlated than stocks across industries. In addition, according to Chan, Lakonishok & Bhaskaran (2007), higher return comovement is more apparent for large-cap stocks than for small-cap stocks of the same industry classification.

Although, existing empirical literature suggests that industry plays a certain role in explaining stock returns; however, it is unclear whether industry-related patterns are consistent with standard asset pricing theories. Since the CAPM or the arbitrage pricing theory attributes the source of asset correlation to the market portfolio or common risk factors, the risk-based asset pricing models indicate the existence of additional risk factors in order to reconcile inconsistencies. For example, according to Chan et al. (2007), if pricing factors fail to explain higher return comovement for large-cap stocks and lower return comovement for small-cap stocks within an industry, then an additional factor is needed. It is difficult to impose economic interpretation for the reason that the systematic risk factors are not observable. Therefore, it is strongly desirable to search for additional factors from economic theories because factors based on the general equilibrium framework naturally have economic interpretations. However, determining what to employ as candidates for additional risk factors is not an easy task since the main focus of economic analysis has been on the aggregate shock. A concept compatible in the finance literature the market portfolio. In fact, because macroeconomists have endeavored to understand the persistence in the aggregate economic activity fluctuations for decades, standard models of business cycles are assumed to have one good, so one sector with one aggregate shock, possibly due to conceptual difficulties.

However, empirical results on the business cycle provide some evidence supporting for multiple sectors and shocks. Although there are some contentions, aggregate shocks alone cannot explain most of the business cycle variation of aggregate activity. [2] A recent study by Atalay (2014) showed that industry-specific shocks account for nearly two-thirds of the volatility of aggregate output. In addition, many models with systematic uncertainty as a single aggregate productivity shock have difficulty replicating the multi-factor structure of return comovement in the data and so fail to match second moments.

To overcome these shortcomings, researchers in macro-finance field begin to employ additional shock structure and bring up so-called investment shock. For example, Long Jr. & Plosser (1983) presented a model of the economy with a collection of perfectly compet-

[2] See, for example, Gal & Rabanal (2005) and Smets & Wouters (2007).

itive industries. Under their framework, many resarhcers including Long Jr. & Plosser (1983) argued that idiosyncratic shocks to industries productivities have the potential to generate substantial aggregate fluctuations.[3] Accordingly, two types of technological innovations are proposed as the key drivers of economic growth and uctuation: disembodied technology shocks that affect the productivity of all rms uniformly, and embodied technology shocks –i.e., investment specific technology (IST) shocks– that aect the productivity of firms within an industry through new capital or equipment. IST shocks have become an important feature of the macroeconomic literature.[4] In addition, corresponding to the empirical findings, the dynamic stochastic general equilibrium literature employing sector-specific shocks is burgeoning. Greenwood, Hercowitz & Krusell (1997) and Greenwood, Hercowitz & Krusell (2000) wrote the representative study to explore IST shocks. Fisher (2006) showed that IST shocks can stand for a large fraction of growth and variations in output. Justiniano, Primiceri & Tambalotti (2010) examine the eect of two investment-specific shocks on business cycles and find that the shock is the most important driver of U.S. business cycle fluctuations in the post-war period.

More recently, nancial economists have highlighted the potential role of investment shocks in explaining asset price anomalies in both the cross section and time series. Since the pioneering work of Berk, Green & Naik (1999), both aggregate productivity and discount rate shocks have been used extensively in the investment-based asset pricing literature.[5] Christiano & Fisher (2003) wrote the rst work to explore the asset pricing implications of IST shocks at the aggregate level. Garleanu & Panageas (2012) study the asset pricing implications of technological growth in a model with two different types of shocks; disembodied productivity shocks and technological innovations. Technological change embodied to capital can be a natural source of comovement among rms with dierent asset composition between growth opportunities and asset in place in rm value.[6] Papanikolaou (2011) explored the implications of these shocks for asset prices in the cross-section of stocks. He introduced investment-specic technology shocks in a two-

[3]See, Horvath (1998), Dupor (1999), Acemoglu, Carvalho, Ozdaglar & Tahbaz-Salehi (2012) and Acemoglu, Ozdaglar & Tahbaz-Salehi (2013).

[4]The argument for industry-specific shocks as the source of business cycles proceeds as follows. Suppose the economy is subject to a large number of industry-specic orthogonal disturbances. Then, these disturbances change the relative productivities of input factors including capital or labor, leading to a reallocation of the factors. That is, industries with falling relative productivities use fewer inputs and industries with rising relative productivities use more inputs.

[5]Kogan & Papanikolaou (2012) provide an excellent survey. Gomes, Ogan & Zhang (2003), Carlson, Fisher & Giammarino (2004), and Zhang (2005) have made significant contributions to the literature.

[6]Laitner & Stolyarov (2003), Jovanovic (2008), Kogan & Papanikolaou (2013) and Kogan & Papanikolaou (2014) are recent examples of asset pricing models with embodied technological change. Kogan & Papanikolaou (2010) use the proxy for IST shock to estimate rms' unobservable growth opportunities.

sector general equilibrium model and derives time series and cross sectional asset pricing implications. In a partial equilibrium setting, Kogan & Papanikolaou (2013) and Kogan & Papanikolaou (2014) explored how IST shocks can explain the value premium in the cross-section and associate IST shocks with rm characteristics, including Tobin's Q, past investment, earnings-price ratios, market betas, and idiosyncratic volatility of stock returns.

To study second moments, our first task is to estimate conditional volatilities and correlations for each industries. As financial liberalization and technological advance accelerated the integration of financial markets around the globe, information regarding the macroeconomic fundamentals of developed economies gets to influence emerging-economy fundamentals, leading to the changes in the emerging market equity returns and volatilities.[7] According to Theodossiou & Lee (1993), the US stock market is the major influencer of volatility to the rest of the financial markets. In this vein, we examined the volatility and the correlation effect from the USA to the Chinese sectors during the 2008-2009 Global financial crisis and the 2010-2011 European debt crisis events. The Chinese stock market makes an interesting experimental environment for our study. Since the establishment of the Shanghai and Shenzhen stock exchanges in the early 1990s, the Chinese stock market has been growing rapidly and attracting foreign investors from around the world.[8]

[7]To fully utilize the information from the second moments, we take parsimonious methodologies when we estimate the conditional expected returns. Volatility is usually modeled as a time-varying function of current information. A large body of literature regarding conditional volatility has been spurredby the emergence of the conditional heteroskedasticity models of Engle (1982) and Bollerslev (1986). Moreover, volatilities of aggregate equity index returns are found to be larger after past negative shocks than after positive shocks. Such an asymmetric effect of volatility spillover can be captured in an exponential GARCH model of Nelson (1991), an asymmetric GARCH model of Engle & Ng (1993), and a GJR or threshold GARCH model of Glosten, Jagannathan & Runkle (1993) and Zakoian (1994). Many studies are therefore focusing on volatility transmission from developed markets (mainly the United States) to emerging markets. See Theodossiou and Lee (1993), Cheung, He & Ng (1994), Kim & Rogers (1995), Bekaert & Harvey (1997), and Ng (2000) for details. Ng (2000) examined volatility spillovers from Japan and the US to six Pacific-Basin equity markets and found that Japan imposes a strong regional impact on the Pacific-Basin markets.

[8]It is noteworthy that at least two interesting features pertain to the Chinese stock market. First, the Chinese market is not fully open to foreigners and exhibiting market segmentation. See Weber & Zhang (2012); Zhou, Zhang & Zhang (2012); To wit, domestic investors trade A-shares in Chinese Renminbi, while foreigners trade B-shares in either US dollars on the Shanghai stock exchange or Hong Kong dollars on the Shenzhen stock exchange. Domestic investors have been allowed to trade B-shares as long as they hold deposit in foreign currency as controls were loosened since 2001. A-shares have also been accessible to some qualified foreign institutional investors (QFII) since 2003. Despite that, the A-shares market is in a much larger size and predominant over the B-shares market. The second feature of the Chinese stock market is the so-called split share structure (Hou & Lee 2014). As compared to the tradable shares held by the public, a large portion of listed A-shares were held by central and local governments and were non-tradable prior to 2005. The China Securities Regulatory Commission (CRSC) began a reform of the split share structure, however, with an official announcement on September 4, 2005. Afterwards, those

We thus examine the dynamic conditional correlations between Chinese industry returns and the representative market index, namely the S&P 500, with data spanning from 2006 to 2014. We employe the Dynamic Conditional Correlation (DCC) model developed by Engle (1982), along with the Asymmetric Dynamic Conditional Correlation (ADCC) model, which was extended by Cappiello, Engle & Sheppard (2006), as our baseline model. In contrast to volatility, correlation studies have received much less attention from academic researchers, despite its pivotal role in nance. To the best of our knowledge, this study is the first to investigate asset pricing implications of the conditional correlation effects at the Chinese sector level.[9] Taking this account, our findings contribute to the existing literature related to volatility and correlation by figuring out what micro-determinants drive co-movement among the sector-level correlations and by explaining the conditional correlations dynamics based on corporate investment and financing activities.

Using a sample of 12 Chinese sector portfolio returns, we document several intriguing findings. First, we find that the conditional correlations significantly vary across sectors and crises. Specifically, the financial and energy sectors persistently exhibit a relatively high correlation, whereas the health and durable sectors persistently preserve a low correlation with S&P 500. In the meanwhile, conditional correlations of most sectors with S&P 500 decreased during the financial crisis and the European debt crisis. To answer the question of what drives different sectoral behaviors, we associate the magnitude difference of the conditional correlations among sectors with different sensitivities to industry-specific shocks within the general equilibrium model as in Papanikolaou (2011). Our finding is that crisis dummies and industry-specific variables proxies for investment or growth opportunities are significantly associated with the magnitude of the conditional correlations.

The rest of the paper is organized as follows. Section 2 introduces the general equilibrium model. Section 3 describes the methodologies of estimating conditional volatilities and correlations. Section 4 summarizes our sample data. Section 5 presents empirical results and section 6 concludes.

1.2 General Equilibrium Model

A correlation tells nothing about the causality between two random variables, nonetheless, the magnitude difference among sectoral correlations can be explained by a set of

non-tradable shares are gradually unlocked and traded in the market

[9]Previous papers focus on the Chinese market-wide index, see, for example, Weber & Zhang (2012), Zhou et al. (2012).

explanatory variables. One of our main objectives is to find what economic determinants can explain the magnitude difference of the conditional correlations of 12 sector returns with a market index. The main difficult part is how to impose the economic interpretation on the magnitude difference of the conditional correlations. For this purpose, we rely on the general equilibrium model suggested by Papanikolaou (2011) with an extension to include a foreign market index. The model is highly stylized in the investment shock related literature.

1.2.1 Household

We assume that there exists a continuum of identical households whose utility is defined recursively as follows:

$$J_t = E_t \int_t^{\infty} u(C_s, N_s, J_s) ds$$

$$\text{where, } u(C, N, J) = \frac{\rho}{1-\theta^{-1}} \left\{ \frac{(CN^{\psi})^{1-\theta^{-1}}}{[(1-\gamma)J]^{\frac{\gamma-\theta^{-1}}{1-\gamma}}} - (1-\gamma)J \right\},$$

C, N, and J are consumption, leisure, and utility index, respectively. A set of model parameters $\Phi = \{\rho, \gamma, \psi, \theta\}$ follow the usual notation, namely time preference, relative risk aversion, elasticity of intertemporal substitution, and relative shares of consumption and leisure, respectively. A household allocates 1-N units of labor between two sectors: a sector producing the consumption (C) good and a sector producing the investment (I) good,

$$L_{C_t} + L_{I_t} = 1 - N_t$$

1.2.2 Firms and shock structures

In the economy, two sectors are assumed to exist and produce goods using Cobb-Douglas technology, sector specific capitals, and labors. The consumption producers are required to buy investment goods from investment good producers to produce consumption goods. The consumption goods sector produces $C_t = A_t K_{C,t}^{\beta_C} L_{C,t}^{1-\beta_C}$ where a disembodied productivity shock evolves according to $dA_t = \mu_A A_t dt + \sigma_A A_t dB_t^A$ and the law of motion for the capital stock is given by $dK_{C,t} = (i_{C,t} - \delta) K_{C,t} dt$. Papanikolaou (2011) proposes a new shock Z_m to change the marginal efficiency of investment: the shock $dZ_{m,t} = \sigma_m Z_{m,t} dB_t^{Z,m}$ whose interpretation is given as an improvement in the quality of investment goods. Under this modeling scheme, firms can increase their capital stock $i_C K_C$ by purchasing

$Z_m^{-1}c(i_C)K_C$ at a relative price p^I. Then, the value of consumption good producers with profit $\pi(\cdot)$ and cost $\chi(\cdot)$ functions is as follows:

$$S_{C,t} = E_t \int_t^\infty \frac{M_s}{M_t}[\pi(A_s, K_{C,s}) - \chi(i_s, K_{C,s})]ds$$

where $\pi(A_s, K_{C,s}) = A_s K_{C,s}^{\beta_C} L_{C,s}^{1-\beta_C}$ and $\chi(i_s, K_{C,s}) = \omega_s L_{C,s} + p_s^I Z_m^{-1} c(i_{C,s})K_{C,s}$ and M denotes the stochastic discount factor from household first-order conditions. Consumption good producers buy $p_s^I Z_m^{-1} c(i_{C,s})K_{C,s}$ amount from investment good producers to produce. The investment goods sector produces $Y_t = Z_{I,t} K_{I,t}^{\beta_I} L_{I,t}^{1-\beta_I}$ where a total factor productivity shock evolves according to $dZ_{I,t} = \mu_Z Z_{I,t}dt + \sigma_Z Z_{I,t} dB_t^A$ Analogous to the value of consumption good producers, the value of investment good producers is given as follows:

$$S_{I,t} = E_t \int_t^\infty \frac{M_s}{M_t}[\pi(Z_{I,s}) - \chi(\cdot)]ds$$

where $\pi(Z_{I,s}) = p_s^I Z_{I,s} K_{I,s}^{\beta_I} L_{I,s}^{1-\beta_I}$ and $\chi(\cdot) = \omega_s L_{I,s}$. It is not mandatory for Investment good producers to buy goods from the consumption sector. Note that there is no capital argument in either profit or cost functions of the investment goods producer for modeling purposes.

1.2.3 Competitive Equilibrium

A representative household problem is equivalent to the social planners problem under the welfare theorem conditions. The planners value function J should satisfy the following Hamilton-Jacobi-Bellman equation:

$$\begin{aligned} 0 = \max_{L_I, L_C, i_C, N} u(C,N,J) + (i_C - \delta)J_{K_C}K_C + \mu_A J_A A + \frac{1}{2}\sigma_A^2 J_{AA}A^2 \\ + \mu_Z J_Z Z + \frac{1}{2}\sigma_Z^2 J_{ZZ} Z^2 \end{aligned}$$

where the social planners value function takes the form $J(A, Z, K_C)_t = \frac{(AK_{C,t}^{\beta_C})^{1-\gamma}}{1-\gamma}h(\Omega)$ and $\Omega = \ln(\frac{ZK_{I,t}^{\beta_I}}{K_C})$.[10] The current state of the economy is contained in the variable Ω

[10] $h(\Omega)$ is the solution to the ordinary differential equation of Appendix A from Papanikolaou (2011). The analytical functional form of $h(\Omega)$ for a special case can be inferred as in Campbell, Chan & Viceira (2003).

thus the state variable Ω captures real investment opportunities.[11] The final piece of the general equilibrium is the stochastic discount factor (SDF), which comes from the household rst-order condition with respect to the consumption as follows:

$$\frac{dM_t}{M_t} = -r_{f,t}dt - b_A dB_t^A - b_Z(\Omega)dB_t^Z$$

where $b_A = \gamma\sigma_A$ and $b_Z(\Omega) \simeq -\left((\cdot) + \frac{\theta^{-1}-\gamma)h'(\Omega)}{(1-\gamma)h(\Omega)}\right)\sigma_Z$.[12] We proceed further to derive the economic meaning of the conditional correlations.

1.2.4 Investment shocks and conditional correlations

Risk premiums are defined as the covariance of asset returns and the stochastic discount factor. Expected excess returns are proportional to the covariance of returns with discount factors as follows:

$$E_t\left[\frac{dS_{i,t} + D_{i,t}dt}{S_{i,t}} - r_{f,t}dt\right] = -Cov_t(\frac{dM_t}{M_t}, \frac{dS_{i,t}}{S_{i,t}})$$

The equation above provides the stochastic differential equations for the asset risk premia of investment and consumption goods firms as below:

$$\frac{dS_{I,t} + D_{I,t}dt}{S_{I,t}} = E_t\left[\frac{dS_{I,t} + D_{I,t}dt}{S_{I,t}}\right] + \sigma_x dB_t^A + \Pi_I(\Omega)\sigma_Z dB_t^Z$$

$$\frac{dS_{C,t} + D_{C,t}dt}{S_{C,t}} = E_t\left[\frac{dS_{C,t} + D_{C,t}dt}{S_{C,t}}\right] + \sigma_x dB_t^A + \Pi_C(\Omega)\sigma_Z dB_t^Z$$

where $\Pi_I(\Omega)$ and $\Pi_C(\Omega)$ are terms to capture the sensitivities to the investment shocks. The two terms are the functions of model parameters $\Phi = \{\rho, \gamma, \psi, \theta\}$ and $h(\Omega)$ from the the social planners value function. Based on these equations, we observe that two different shocks have different effects on the stock returns. An investment shock Z affects differently to the value of the investment good firm and that of the consumption good firm due to the existence of different sensitivities in each sectors, equivalently due to the existence of the roles of $\Pi_I(\Omega)$ and $\Pi_C(\Omega)$. On the other hand, a total productivity shock to the consumption sector has a symmetric effect on both sectors. In addition, the value of the market portfolio is defined as the sum of the values of two sectors. Based on these theoretical derivations, we explore asset pricing implications in terms

[11]Since both shocks $Z_{I,t}$ and $Z_{m,t}$ capture the trade-off between consumption and capital, combining two shocks leads to $Z_t = Z_{I,t}Z_{m,t}$whose interpretation is given as the investment shock.

[12]Refer to Papanikolaou (2011) for technical conditions.

of the second moments instead of constructing a portfolio of long investment and short consumption stocks as in Kogan & Papanikolaou (2010), or relying on direct measure of IST shocks as in Greenwood et al. (1997). As explained in the introduction, we use the conditional correlations as our direct comovement measures between industry portfolios and representative market indices as a proxy for the common risk factor. From the two stochastic differential equations above, we have the following conditional covariance expression for each sector $i = \{I, C\}$:

$$Cov_t\left(\frac{dS_{i,t}}{S_{i,t}} - E_t\left[\frac{dS_{i,t}}{S_{i,t}}\right], \frac{dS^F_{M,t}}{S^F_{M,t}} - E_t\left[\frac{dS^F_{M,t}}{S^F_{M,t}}\right]\right)$$

$$= Cov_t\left(\sigma_A dB^A_t + \Pi_I(\Omega)\sigma_Z dB^Z_t, \sigma^F_X dB^{FA}_t + \Pi^F_M(\Omega^F)\sigma^F_Z dB^{FZ}_t\right)$$

Note that we employ the market index, the S&P 500 as our common risk factor with superscript F. From the above equation, the magnitude difference can be defined as $(\Pi_I(\Omega) - \Pi_C(\Omega))\left\{\sigma_A\sigma^F_Z Cov_t(dB^A_t, dB^{FA}_t) + \Pi^F_M(\Omega^F)\sigma_Z\sigma^F_Z Cov_t(dB^Z_t, dB^{FZ}_t)\right\}$ From this result, we can impose the economic interpretation on the magnitude difference of the conditional correlations among sectors. The key determinant of the magnitude difference comes from the difference term, $\Pi_I(\Omega) - \Pi_C(\Omega)$ Industry portfolios whose characteristics are close to investment good producers will exhibit higher conditional covariance, and thus higher conditional correlations. On the other hand, industry portfolios whose characteristics are close to consumption good producers will show lower conditional correlations. Empirical observations indicate that $\Pi_I(\Omega) - \Pi_C(\Omega)$ term usually takes the positive sign. This theoretical derivation is compatible with the results of the literature related to growth opportunity and technology shock. That is, the sensitivity of firm stock returns to investment-specific shocks is greater for firms with a relatively large ratio of growth opportunities over assets in place. We measure the unobservable asset composition through a lens of the magnitude difference of the conditional correlations. With this conjecture in mind, we turn to the estimation of the conditional correlations of sector portfolios with a market index.

1.3 Estimation Specifications

We employ the Dynamic Conditional Correlation (DCC) model by Engle (2002) and the Asymmetric Dynamic Conditional Correlation (ADCC) model extended by Cappiello et al. (2006) as our baseline model for several reasons. The first reason is the empirical performance suggested by Laurent, Rombouts & Violante (2012). Based on the model confidence set (MCS) and the superior predictive ability (SPA) tests, they find that the best models do not provide a significantly better forecasts than the DCC model with leverage effect in the conditional variances. Another reason for utilizing the DCC model is a modeling parsimony. Since most conditional volatility and correlation analysis is based on multivariate GARCH-type models with a possible curse of dimensionality, flexibility is important in terms of parsimony. Rather than estimating the covariance matrix and then calculating the conditional correlations from it, the DCC model estimates the correlation matrix directly by using the standardized residuals. This gives rise to high flexibility by reducing the number of parameters to estimate.[13] Adding to the DCC model analysis, the ADCC model is also considered to incorporate the growing empirical evidence that the financial market correlations become more volatile during negative situations such as the financial crisis. To keep our models parsimonious, the stochastic evolution of the conditional mean and volatility equations are assumed to follow ARMA (1,1) and GJR-GARCH (1,1) respectively. We further assume that the k dimensional vector of asset returns r_t is conditionally normally distributed with mean zero and covariance matrix Ω_t Then, conditional means, variances and covariances in our model specifications are given as below:

$$\begin{bmatrix} r_{US,t} = \Phi_{US} r_{US,t-1} + \Lambda_{US}\varepsilon_{US,t-1} + \varepsilon_{US,t} \\ r_{i,t} = \Phi_i r_{i,t} + \Lambda_i \varepsilon_{i,t} + \varepsilon_{i,t} \end{bmatrix}, \begin{bmatrix} \varepsilon_{US,t} \\ \varepsilon_{i,t} \end{bmatrix} \sim N(0, \Omega_t)$$

As described in the introduction, our market equity return of interest is the United States working as the sources of outer shock. The 12 Chinese sector indices are categorized following the same methodology based on the SICC codes as in the Fama-French 12 industries portfolio. The above equations can be described using a vector notation as follows:

$$\mathbf{r_t} = \boldsymbol{\Phi}\mathbf{r_{t-1}} + \boldsymbol{\Lambda}\varepsilon_{\mathbf{t-1}} + \varepsilon_{\mathbf{t}}, \varepsilon_{\mathbf{t}} \sim N(0, \Omega_t)$$

Following Engle (2002), the conditional covariance matrix Ω_t can be decomposed into $\Omega_t = D_t R_t D_t$ the product of the conditional standard deviations $D_t = \text{diag}\{\sigma_{it}\}$ and the conditional correlations $R_t = \text{diag}\{\rho_{ijt}\}$. Matrix operator diag$\{A\}$ creates a diagonal matrix asset from the matrix A and R_t is the dynamic conditional correlation matrix. The Dynamic Conditional Correlation (DCC) representation focuses on the time-varying

[13] The number of parameters to be estimated is (N+1)(N+4)/2, which is relatively smaller than the complete BEKK form, another alternative for the correlation modeling, with the same dimension when N is small.

dynamics of R_t whose specification is given by the following:

$$
\begin{aligned}
R_t &= Q_t^* Q_t Q_t^*, \\
Q_t &= (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\bar{Q} + \sum_{m=1}^{M} \alpha_m \left(u_{t-m} u_{t-m}^{'} \right) + \sum_{n=1}^{N} \beta_n Q_{t-n} \\
Q_t^* &= (Q_t \odot I_k)^{-0.5}
\end{aligned}
$$

[14] where $u_t = D_t^{-1}(r_t - \mu_t)$ is the k by 1 vector of standardized innovations whose i-th element is given by $u_{i,t} = \epsilon_{i,t}/\sqrt{\sigma_{ii,t}^2}$ and ϵ_t is a sequence of i.i.d innovations with mean 0 and unit variance. μ_t can be any adapted model for the conditional mean equation and we have employed ARMA (1, 1) for our base mean equation. Let $\bar{Q}$ be the unconditional correlation matrix of the normalized residuals and then, $\bar{Q}$ can be obtained by calculating the sampling mean using $u_t u_t^{'}/T$.[15] Parameter restrictions on 1) stationarity constraint: positive coefficients of unconditional correlation matrix, and 2) positivity constraint: non-negative coefficients of symmetric innovations and lagged correlations should be taken into considerations to guarantee a positive definite Q_t matrix. Moreover, R_t matrix is positive definite if and only if Q_t matrix is a positive definite.

The estimation procedure suggested by Engle & Sheppard (2001) is being done in three stages. In the first stage of the DCC estimation, we fit univariate GARCH models for each of the four variables. In the second stage, the intercept parameters – that is, the unconditional correlation matrix of the standardized residuals and in the final stage, the coefficients governing the dynamics of the conditional correlations – are estimated using quasi-maximum likelihood.[16] For these three procedures to complete, model specifications on the conditional variance are needed. Optimal lags in the univariate volatility specifications are selected based on the Akaike Information Criterion (AIC) or the Bayesian information criterion (BIC) and any univariate GARCH processes that are covariance stationary and assumes normally distributed errors can be used to model the conditional variances. Following Laurent et al. (2012)'s result, we have chosen the GJR-GARCH model for our base volatility equation. The GJR-GARCH by Glosten, Jagannathan, and Runkle (1993) extended the standard GARCH-type model, including asymmetric terms

[14] Q_t^* guarantees that the conditional correlation matrix R_t is well-defined with unit value on the diagonal and values ranging from -1 to 1 on the off-diagonals. $\odot$ denotes the Hadamard product (element-by-element multiplication).

[15] The conditional covariance matrix $\Omega_t = D_t R_t D_t$, is positive definite when R_t is positive definite and the GARCH specifications are correct.

[16] See Engle & Sheppard (2001) for more details.

to capture a common feature known as the "leverage effect".[17] The GJR-GARCH process is defined as below:

$$\sigma_t^2 \omega + \sum_{p=1}^{P} \phi_p \varepsilon_{t-p}^2 + \sum_{o=1}^{O} \gamma_o \varepsilon_{t-o}^2 I_{\{\varepsilon_{t-o}<0\}} + \sum_{q=1}^{Q} \varphi_q \sigma_{t-q}^2$$

where $I_{\{\varepsilon_{t-o}<0\}}$ is an indicator function that takes the value 1 if $\varepsilon_{t-o} < 0$ and 0 otherwise. The complete parameter restrictions to ensure the positive definite conditional variance in the GJR-GARCH (P,O,Q) are not easy to determine, though it is simple for the GJR-GARCH (1,1,1). To avoid computational burden, we direct our interest only to the GJR-GARCH (1,1,1) model whose parameter restrictions are simply given by $\omega > 0, \phi_1 \geq 0, \varphi_1 \geq 0$ and $\phi_1 + \gamma_1 \geq 0$.[18]

To investigate further the properties of sector equity returns, we additionally adopt the Asymmetric Dynamic Conditional Correlation (ADCC) model. The ADCC model is an extended version of the DCC model by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation. The ADCC model dynamics are given as:

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n) \bar{Q} - \sum_{k=1}^{K} \zeta_k \bar{N} + \sum_{m=1}^{M} \alpha_m \left(u_{t-m} u_{t-m}^{'} \right) + \sum_{k=1}^{K} \zeta_k \left(n_{t-k} n_{t-k}^{'} \right) + \sum_{n=1}^{N} \beta_n Q_{t-n}$$

where $n_{t-k} = I_{\{\varepsilon_{t-k}<0\}} \odot \varepsilon_{t-k}$ with being an indicator function. $\bar{N}$ is the unconditional covariance matrix and $\bar{N}$ can be obtained by calculating the sampling mean using $n_t n_t^{'}/T$. [19]

1.4 Data and sample

We collected weekly total return index (RI), which is originally constructed by the Thomson Reuters DataStream and measured a theoretical growth in the individual stock value, and the market value (MV) of Chinese A-share stocks.[20] The return index and the market

[17] The leverage effects captures the propensity for the volatility to rise more subsequent to large negative shocks than to large positive shocks.

[18] If the innovations are conditionally normal, a GJR-GARCH model will be covariance stationary as long as the parameter restriction are satisfied and $\phi_1 + 0.5\gamma_1 + \varphi_1 \leq 1$

[19] Refer to Cappiello et al. (2006) for a detailed necessary and sufficient condition for Q_t to be positive definite.

[20] B-shares are mainly traded by foreigners under a different trading system from A-shares. B-shares are also known to be traded at a discount (see, for example, Bailey, Chung & Kang (1999) ; Chan, Menkvled & Yang (2008)). We thus remove B-shares from our sample by examining stocks names. We also drop securities that are not common equity, not incorporated in China, etc. We then use the remaining

value are denominated in Chinese Renminbi to avoid the impact of foreign exchange rate. Individual stock returns are computed as the logarithm of (RI_t/RI_{t-1}). To categorize individual stocks into sectors, we follow Fama and Frenchs classification of 12 industries based on the 4-digit SIC codes, which are obtained from the Worldscope. The 12 industries are consumer nondurables (nodur), consumer durables (durbl), Manufacturing (manuf), oil, gas, and coal extraction and products (enrgy), chemicals and allied products (chems), business equipment (buseeq), telephone and television transmission (telcm), utilities (utils), whose sale, retail, and some services (shops), healthcare, medical equipment, and drugs (hlth), finance (money), and other. We computed sector-level returns by averaging individual firm returns in each sector and weighting the returns by their market value at the end of the previous trading day to minimize any potential size effect.

We also gathered the weekly price index (PI) of the market-wide equity indices in local currencies from the DataStream and computed index returns as the logarithm of (RI_t/RI_{t-1}). The price index is adjusted for capital action and weighted by market value. The equity indices analyzed in this study are the S&P500 index and Shanghai Stock Exchange A share index, which are most widely used to proxy for the American and Chinese stock markets. We employ the S&P 500 index as the source of outside shocks to the Chinese stock market. Our sample period starts in January 2006 and ends in December 2014. To obtain more accurate estimates based on multivariate GARCH models, we need to use as many observations as possible. If the study period is too long, however, the estimates may not precisely capture the time-varying features. Considering the structural and institutional change in the Chinese stock market, we thus focus on a post-reform period during which the market liquidity has increased dramatically and the stock market became more sensitive to information shocks.

We also focus on the two crisis periods, namely, the global financial crisis and the European sovereign debt crisis. The global financial crisis started in August 2007, became more severe in September 2008 with the collapse of Lehman Brothers, and exported its shocks to worldwide in late 2008 and early 2009. With the effects of the global financial crisis across the Euro area, according to Lane (2012), the on-going European debt crisis erupted in late 2009. In response to the crisis, Greece was shut out of the bond market in May 2010, followed by Ireland in November 2010 and Portugal in April 2011. Spain and Cyprus also requested bailouts in 2012. Taking into account of the timelines of the two crises, we mainly examined the correlation dynamics for 2008-2009 and 2010-2012, respectively.

DataStream codes as identifiers to retrieve data from the Thomson Reuters DataStream.

Table 1: Summary statistics of the sample

Panel A: Summary statistics of individual stock returns in each industry					
Industry	# of firms	Mean	Stddev	Skewness	Kurtosis
Nondurables	179	0.22%	4.976	0.595	5.752
Durables	107	0.25%	4.938	0.639	4
Manufacturing	421	0.23%	5.076	0.711	7.5
Energy	55	0.18%	4.779	0.523	3.348
Chemicals	158	0.21%	4.989	0.615	5.373
Business equipment	234	0.24%	5.228	0.577	5.794
Telecommunication	11	0.27%	4.838	0.281	0.925
Utilities	66	0.22%	4.452	0.548	4.104
Shops	181	0.24%	5.001	0.66	6.212
Health	123	0.34%	4.83	0.531	4.878
Money	53	0.30%	4.922	0.658	3.812
Others	372	0.23%	5.115	0.909	10.206

Panel B: Summary statistics of market indices and industry returns				
Index	Mean	Stddev	Skewness	Kurtosis
S&P500	0.11%	2.537	-0.914	9.501
SSEPI	0.18%	3.6	-0.024	1.82
Nondurables	0.19%	3.983	-0.235	1.365
Durables	0.19%	4.439	-0.244	2.419
Manufacturing	0.10%	4.347	-0.301	1.835
Energy	0.05%	4.108	0.199	2.123
Chemicals	0.06%	4.208	-0.611	1.279
Business equipment	0.11%	4.449	-0.58	1.336
Telecommunication	0.10%	4.104	-0.298	1.261
Utilities	0.10%	3.643	-0.602	3.431
Shops	0.11%	4.03	-0.377	1.933
Health	0.24%	4.165	-0.441	1.707
Money	0.17%	4.115	0.448	3.959
Others	0.08%	4.067	-0.382	2.008

Note. This table presents summary statistics of weekly log returns of individual stocks in each industry (in Panel A) and of value-weighted market indices and Chinese industry returns. The 12 industries are classified based on stocks' 4-digit SIC codes following Fama and French's criteria. The S&P500 and SSEPI are value-weighted market-wide indices in America and China, respectively. The sample period is from January 1, 2006 to December 31, 2014.

Table 1 contains the summary statistics of our sample. There are in total 1961 individual stocks that issue A-shares and are covered by the DataStream. As shown in Panel A, stocks are unevenly distributed across the 12 industries - For example, 421 stocks fall into the manufacturing industry, and only 11 stocks in the telecommunication industry. Not surprisingly, the cross-sectional distribution (i.e., mean, standard deviation, skewness, and kurtosis) of weekly log returns varies across industries. For example, individual stocks in the health industry produce the highest weekly return of 0.335%; individual stocks in the energy industry yields the lowest weekly return of 0.182%. Panel B shows summary statistics of value-weighted market-wide equity indices and industry returns. Weekly returns of the S&P500 averaged to 0.113% over our sample period. Weekly returns of the Shanghai A share index averaged to 0.180%. Consistent with the pattern of individual stocks returns, the health industry index earns the highest return of 0.235%, whereas the energy industry index yields the lowest return of 0.046%.

1.5 Empirical Results

1.5.1 Conditional correlation dynamics and crises

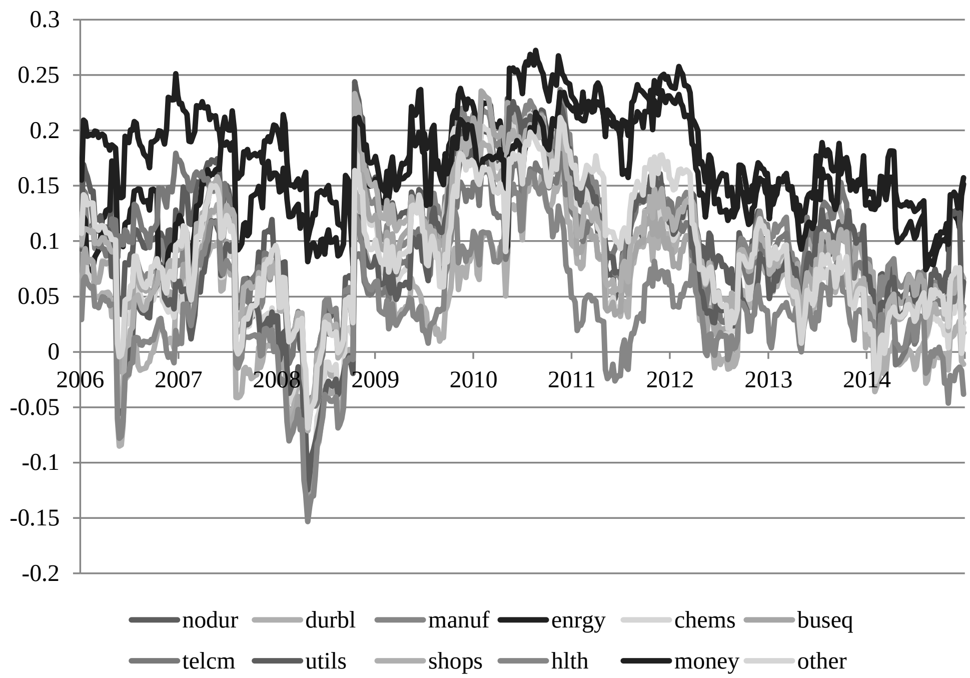
Figure 1 plots the sector-level conditional correlations with the S&P 500 index over the period of 2006 to 2014 and Table 2 summarizes estimates of parameters for the Shanghai A-share composite index and 12 sector indices.[21] The figure captures some interesting patterns. First, the conditional correlations between Chinese sector returns and the S&P 500 index returns reveal an unstable time-variation that includes asymmetric dynamics. In particular, the time-varying correlations were relatively low before and during the 2008-2009 global financial crisis period. This is consistent with the empirical observation that China was not one of the countries hardest hit by the crisis.[22] As noted earlier, the sector returns from health, utilities, durables, and shops even negatively comove with the S&P 500 index returns in 2008. The comovement between Chinese sector returns and the S&P 500 index returns increased after 2009. Then, the magnitude of the conditional correlations decreased during the 2010-2011 European debt crisis. This time-series patterns exists for every crisis.

It is also interesting to observe that Chinese sectors respond to the crises in different patterns. The difference in their responding behaviors strongly surfaces around the days of

[21] Most estimates of parameters for the Shanghai A-share composite index and 12 sector indices exibit persistent behavior, consistent to the volatility estimates

[22] China continued to have one of the highest rates of economic growth across the globe, recording 9.6% in 2008 and 9.2% in 2009

Figure 1: Sector-level dynamic conditional correlations with the S&P500 index



Note. This figure plots sector-level dynamic conditional correlations with the S&P 500 index estimated by the DCC model. The sample consists of the conditional correlations of 12 sectors, as described in the caption of Table 1. The sample period spans from January of 2006 to December of 2014.

Table 2: Estimates of DCC and ADCC models

	DCC estimates				ADCC estimates					
Sectors	α_1	S.E	β_1	S.E	ς_1	S.E	β_1	S.E		S.E
Shanghai Index	0.006***	-0.0019	0.9791***	-0.0054	0.0013	-0.0029	0.012	-0.0076	0.9743***	-0.0106
Nondurables	0.0057***	-0.0018	0.9756***	-0.0061	0.0015	-0.0028	0.0112	-0.0078	0.9717***	-0.014
Durables	0.0064***	-0.0022	0.9775***	-0.007	0.0022	-0.0025	**0.0103***	-0.0055	0.9753***	-0.0101
Manufacturing	0.0066***	-0.0022	0.9749***	-0.0091	0.0032	-0.0026	**0.0093***	-0.0056	0.9704***	-0.0125
Energy	0.0053***	-0.0019	0.9838***	-0.0062	0	-0.004	**0.0143***	-0.0085	0.978***	-0.0096
Chemicals	0.0062***	-0.0023	0.9744***	-0.0084	0.0023	-0.0023	**0.0092****	-0.0045	0.9738***	-0.0109
Business equipment	0.0057***	-0.0021	0.9776***	-0.0088	0.0029	-0.0022	0.0067	-0.0044	0.9766***	-0.0096
Telecommunication	0.0054***	-0.002	0.98***	-0.0068	0.0007	-0.0023	**0.0119***	-0.0065	0.9771***	-0.0102
Utilities	0.0074***	-0.0021	0.9733***	-0.0075	0.0037	-0.0035	0.0093	-0.0137	0.9705***	-0.0212
Shops	0.0057***	-0.0023	0.978**	-0.0076	0.0019	-0.0027	0.0099	-0.0066	0.9737***	-0.0122
Health	0.0062***	-0.0024	0.971***	-0.0105	0.0015	-0.005	0.0107	-0.0165	0.9723***	-0.021
Money	**0.0063*****	**-0.0016**	**0.9768*****	**-0.0044**	**0.0005**	**-0.0022**	**0.013*****	**-0.0042**	**0.9767*****	**-0.0058**
Others	0.0063***	-0.0019	0.9789***	-0.0067	0.003	-0.1777	0.0087	-0.4123	0.9752***	-0.262

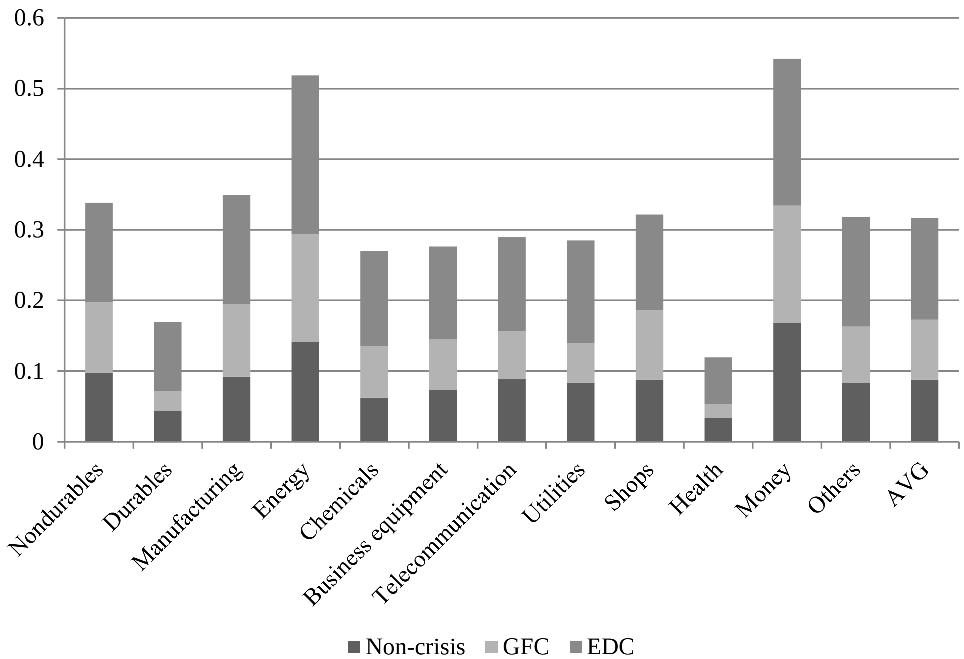
Note. This table summarizes estimates of parameters for the Shanghai A-share composite index and 12 sector indices. Estimates are obtained by employing the dynamic conditional correlation (DCC) and asymmetric dynamic conditional correlation (ADCC) models. DCC-type models decompose the conditional covariance into conditional variances and the conditional correlation. The GJR-GARCH model is employed for the conditional variance model, although we do not report the related parameters to keep our focus on the correlation dynamics. Parameter α_1 captures the effect of the conditional correlation innovations and β_1 captures the effect of the lagged conditional correlation. Parameter ς_1 in the ADCC estimation result captures the asymmetric effects in the innovations. The 12 industries are classified based on stocks' 4-digit SIC codes following Fama and Frenchs criteria. The S&P 500 and SSEPI are value-weighted market-wide indices in America and China, respectively. The sample period is from January 1, 2006 to December 31, 2014. The definitions of the variables in these regressions are provided in Table 1. The numbers in the parentheses are robust standard errors. *, ** and *** indicate two-tailed significance at the 10%, 5% and 1% levels, respectively.

the Lehman Brothers collapse. For example, when the Lehman Brothers fell in September 2008, the Chinese money sector returns instantly jumped to the higher magnitude. In contrast, the Chinese nondurable sectors response was relatively stable and the conditional correlation of the nondurable sector decreased during the European debt crisis. As shown in Figure 1, the sector-level correlations with the outside shock were affected by the crises with different degrees. The magnitude of the conditional correlations was relatively low during the financial crisis period, but gradually increased after Lehman Brothers collapsed. The correlations peaked during the European debt crisis. The energy sectors response verifies a gradual increase in its correlations. The peak of the energy sectors correlations was not around the Lehman Brothers fall. Instead, the peak kept increasing its height over time. However, the financial sectors correlation reached its peak around the Lehman Brothers collapse and stopped increasing.[23] Figure 2 confirms the different magnitude of the conditional correlations for all industries. Figure 2 plots the mean values of the conditional correlations of each sector across the non-crisis, global financial crisis (GFC), and European debt crisis (EDC) periods.

In addition to these time-series dynamics, it is noticeable that the correlations tend to comove across the 12 industries. It implies that the Chinese sector returns comoved with each other, and therefore responded to the outside shock in qualitatively the same way. This is compatible with the firm level theory of comovement of stock returns among firms with similar characteristics. Last but not least, the most notable pattern points to the difference in the magnitude of correlations across the 12 sectors. For example, the money and energy sectors maintained relatively higher co-movement with the outside shock, whereas health, utilities, durables, and shops sectors exhibited relatively lower co-movement with the outside index returns over the whole sample period. This observation was also persistent over all sample periods. Since one of the main objectives of our paper is to investigate the question of what drives this magnitude difference, we combine the economic implications from Papanikolaou (2011) for the magnitude difference of the conditional correlations with investment or growth opportunities

[23]This may be explained by the "averaging out" effect in composing the country-level index with several sector-level indices. Another possible explanation for this discrepancy is that since the products and services in the financial sector are homogeneous and so globally closely intertwined due to the technological advances, the financial sector's response to the outer shocks could be simultaneous and concurrent. Furthermore, the nondurable sector's response itself is far from being the same as the financial sector's response, because the nondurable sector is least dependent on the financial sector. For example, durable goods can usually be rented or bought, while nondurable goods are generally not rented and require no financing activities.

Figure 2: Unconditional mean of 12 conditional correlations estimates



Note. This figure plots averages of sector-level dynamic conditional correlations with the S&P 500 index estimated by the DCC model over the non-crisis, global financial crisis and European debt crisis periods. The sample consists of the conditional correlations of 12 sectors, as described in the caption of Table 1, over the period of January 2006 to December 2014. The financial crisis period is defined to be from January of 2008 to December of 2010 and the European debt crisis period is defined to span from January of 2011 to December of 2012.

1.5.2 Conditional correlations and growth opportunities

A general equilibrium model, as proposed by Papanikolaou (2011), suggests that investment shocks improving real investment opportunities benefit firms producing investment goods relative to firms producing consumption goods. Therefore, the value of growth opportunities can be increased more, compared to the value of existing assets. Based on Papanikolaou (2011)'s two-sector model, we find that sector-level correlations with outside shocks can be associated with the sector-level investment or growth opportunities. As shown in Kogan & Papanikolaou (2013), firm characteristics such as valuation ratios, past investment, profitability, market beta, and idiosyncratic volatility are highly correlated with the ratio of growth opportunities to the firm value. Thus, it is natural to examine the association between the difference in magnitude of sector-level correlations and sector-level growth opportunities.[24]

Growth opportunities can usually be measured by firm-level variables, such as book-to-market ratio, Tobin's Q, capital expenditure, ratio of long-term debt, and growth rate of total assets. Specifically, book-to-market ratio and Tobin's Q directly measure investment opportunities faced by the sectors. The better the investment opportunities, the higher Tobins Q, and the lower the book-to-market ratio. In addition, when the sectors are expected to experience good growth opportunities, they make more investment and thus their capital expenditures are high. Accordingly, to finance their investment outlay, sectors may make more long-term debts and bear a higher long-term debt ratio. More investments also lead directly to a higher growth rate of firm size in those sectors.

Taken together, we construct the five measures of industry-level growth opportunities by utilizing firm-level accounting variables. But the firm-level accounting variables, unlike correlations estimated at weekly frequencies based on stock returns, firm-level accounting variables are generally disclosed at relatively long frequencies, such as annual, semiannual, or quarterly. To have as many observations in our sample as possible, we obtain quarterly financial statements of the Chinese individual firms from the Compustat Global. Specifically, book-to-market ratio (BTM) is computed as the book value of equity over market value of equity; Tobin's Q (TQ) is computed as total assets minus common equity plus the market value of equity and divided by total assets; capital expenditure (Capx)

[24] News that volatility and correlations will be higher in the future will induce risk-adverse investors to sell positions today until the expected return rises to compensate for the risk or the corporate managers adjust their investment decisions to prepare for the future shocks. Hence, markets decline before volatility increases and the firm investment behavior changes before correlation increases. A related claim is the volatility feedback effect, that is, following a negative return shock and an increase in variance, the required rise in expected return creates more volatility.

Table 3: Comparisons of growth opportunity measures between low and high DCC sectors

	BTM	TQ	Capx	Ldebt	Gsize
High DCC sectors	0.711	2.547	0.53	0.32	0.036
Low DCC sectors	0.644	2.671	0.251	0.213	0.033
Difference	0.067	-0.124	0.279	0.107	0.003
t-stat	[2.23]	[-1.55]	[1.19]	[2.35]	[1.28]

Note. This table presents comparisons of growth opportunity measures between low and high DCC sectors. We consider five measures of growth opportunities, book-to-market ratio (BTM), Tobins Q (TQ) computed as (market value of equity + total assets book value of common equity)/ total assets, the ratio of capital expenditure over net value of plant, property, and equipment (Capx), the ratio of long-term debt over equity (Ldebt), and logarithm growth rate of total assets (Gsize). Due to the availability of accounting data, the money sector is not analyzed. In each quarter, we sort the remaining 11 sectors into tertiles based on their conditional correlations, we then average each of the investment opportunities measures for each tertile. We also report the differences of each measure between the high and low DCC sectors and their t-stats in brackets. The sample period is from January of 2006 to December of 2014.

is a ratio of capital expenditure over the net value of plant, property, and equipment; long-term debt (Ldebt) is a ratio of long-term debt over common equity; and finally, a growth rate of size (Gsize) is the logarithm growth rate of individual firms total assets. Due to the unavailability of accounting data for the money sector, we have 11 sectors only with investment opportunity measures.

We compare different measures of growth opportunities across high and low correlation sectors. Specifically, we group quarter-end estimates of sector-level correlations into high, middle and low groups and compare the means of growth opportunities measures. The results are presented in Table 3. Consistent with our hypothesis, the comparisons show that sectors with high correlations bear significantly higher book-to-market ratios and long-term debt/equity ratios than low correlation sectors. High correlation sectors also show higher capital expenditure, higher growth rate of size, and lower Tobin's Q.

1.5.3 Panel regression results

From the above arguments, firstly, we associate the dynamics of sector-level conditional correlations with some common factors that drive the co-movement of correlations across sectors. Next, we connect variations of sectoral correlations to some industry-specific growth opportunities. To further examine the relationship between the sector-level conditional correlations and the related factors during the crises, we associate those conditional correlations with crisis dummies along with industry-level attributes by conducting a battery of panel regression analyses. To be specific, we take the following panel regression model into account:

$$\rho_{it} = \alpha_i + \beta_p (GO)_{i,t-p} + \gamma_1 (GFC)_t + \gamma_2 (EDC)_t + \eta_j (macrp_j)_t + \xi_f (firm_f)_t + \varepsilon_{i,t}$$

where the dependent variables are quarter-end conditional correlation estimates for industry i. The main variables of interest in this study are growth opportunities (GO), measured by BTM, TQ, Capx, Ldebt, and Gsize, respectively. To capture the lag effect of those variables on the conditional correlations, we include contemporaneous, one-quarter, two-quarter, three-quarter, and four-quarter lagged GO in the panel regressions. Given the impact of crises on conditional correlations, we control for the crises impact by including two dummies, GFC and EDC. GFC takes a value of one for years 2008 and 2009 and zero otherwise; EDC equals one for years 2010 and 2011 and equals zero otherwise. We also control for macro effect and introduce the growth rate of GDP, CPI, and real lending rate into the regressions. Finally, we control for firm-level effect, which are firm sizes and gross profit margins.

The fundamental interpretations of the relationship between conditional correlations and sector-level investment opportunities are as follows. As suggested by the two-sector equilibrium model, the magnitude difference of correlations resides in the difference between the two sensitivity terms, $\Pi_I(\Omega) - \Pi_C(\Omega)$. Sectors closer to investment good producers would exhibit higher conditional covariances and thus higher conditional correlations. On the other hand, sectors closer to consumption good producers would show lower conditional correlations. This implies that the sensitivity of returns to investment shocks is greater for sectors or firms with a larger ratio of growth opportunities over asset in place.

Panel regression results with industry-fixed effect are shown in Table 4. We apply various measures of growth opportunities and the results are presented in Panel A, B, C, D, and E, respectively. As shown in Panel A, the book-to-market ratio is negatively correlated with correlations. Particularly, the coefficients of the 2-, 3-, and 4-quarter lagged book-to-market ratios are significantly negative. This indicates that the sectors with lower book-to-market ratios, which face greater growth opportunities, tend to comove highly with the outer shock.[25] The positive statistical significance of the book-to-market variable indicates that smaller book-to-market with a big chance of growth opportunities

[25] The interpretation of the book-to-market variable has been somewhat tricky as pointed out by many researchers. It is taken to indicate the value that the market places on the common equity or net assets of a company (Lee & Makhija 2009) or as a reflection of the ability of managers to use assets effectively and to grow the firm; In addition, the book-to-market ratio is linked to the risk (Griffin & Lemmon (2002); Liew & Vassalou (2000).)

Table 4: Panel regression results of sectors conditional correlations

Panel A: Regressions on BTM						Panel B: Regressions on Tobin's Q					
Model	-1	-2	-3	-4	-5	Model	-1	-2	-3	-4	-5
Dept Var	ρ	ρ	ρ	ρ	ρ	Dept Var	ρ	ρ	ρ	ρ	ρ
BTM0	-0.011					TQ0	**0.004****				
	[-1.589]						**[2.389]**				
BTM-1		-0.012				TQ-1		-0.001			
		[-1.649]						[-0.369]			
BTM-2			**-0.039*****			TQ-2			0.001		
			[-4.880]						[0.466]		
BTM-3				**-0.039*****		TQ-3				0.002	
				[-7.250]						[0.652]	
BTM-4					**-0.034*****	TQ-4					0.005
					[-5.696]						[1.676]
GFC	-0.006	-0.006	-0.012	-0.011	-0.009	GFC	-0.005	-0.004	-0.005	-0.004	-0.005
	[-0.865]	[-0.868]	[-1.654]	[-1.632]	[-1.391]		[-0.744]	[-0.536]	[-0.712]	[-0.641]	[-0.787]
EDC	0.041***	0.041***	0.037***	0.038***	0.038***	EDC	0.042***	0.046***	0.044***	0.044***	0.042***
	[5.663]	[5.296]	[4.931]	[4.892]	[4.938]		[5.983]	[6.733]	[6.099]	[5.511]	[5.042]
gr_GDP	0.458*	0.496**	0.624***	0.789***	0.883***	gr_GDP	0.461**	0.482**	0.474**	0.522***	0.627***
	[2.172]	[2.645]	[3.730]	[5.401]	[6.062]		[2.287]	[2.530]	[2.624]	[3.230]	[3.693]
gr_CPI	-4.664***	-4.766***	-4.899***	-4.696***	-4.549***	gr_CPI	-4.567***	-4.458***	-4.491***	-4.551***	-4.587***
	[-5.392]	[-5.068]	[-5.428]	[-5.357]	[-5.227]		[-5.683]	[-5.253]	[-5.233]	[-5.125]	[-5.175]
RI	-4.821***	-4.888***	-4.721***	-4.424***	-4.357***	RI	-4.692***	-4.596***	-4.592***	-4.652***	-4.634***
	[-4.332]	[-4.136]	[-4.273]	[-4.102]	[-4.006]		[-4.475]	[-4.193]	[-4.205]	[-4.154]	[-4.118]
size	-0.008	-0.006	-0.006	0.004	0.01	size	-0.008	-0.004	-0.007	-0.003	0.001
	[-0.286]	[-0.245]	[-0.231]	[0.154]	[0.434]		[-0.295]	[-0.176]	[-0.297]	[-0.137]	[0.023]
gp	0.010***	-0.007	-0.003	-0.004	0	gp	0.010***	-0.006	-0.002	-0.004	0
	[4.568]	[-1.299]	[-0.744]	[-0.882]	[0.187]		[4.347]	[-1.147]	[-0.432]	[-0.680]	[0.118]
Constant	0.39	0.384	0.389	0.283	0.214	Constant	0.365	0.343	0.362	0.329	0.282
	[1.367]	[1.419]	[1.497]	[1.177]	[0.940]		[1.340]	[1.350]	[1.439]	[1.347]	[1.158]
Obs.	440	440	440	440	440	Obs.	440	440	440	440	440
Number of industries	11	11	11	11	11	Number of industries	11	11	11	11	11
Adj.R^2	0.46	0.452	0.473	0.47	0.465	Adj.R^2	0.461	0.448	0.447	0.447	0.449
Industry FE	YES	YES	YES	YES	YES	Industry FE	YES	YES	YES	YES	YES

Note. This table presents panel regression results with the industry-fixed effect. We regress sectors conditional correlations on sector-level growth opportunity variables while controlling for crisis dummies, macro variables and firm-level characteristics. The regression model is given by

$$\rho_{it} = \alpha_i + \beta_p(GO)_{it-p} + \gamma_1(GFC)_t + \gamma_2(EDC)_t + \eta_j(macro_j)_t + \zeta_f(firm_f)_t + \varepsilon_{it},$$

where ρ_{it} stands for quarter-end estimates of the conditional correlations with S&P 500 from the DCC model. Sector-level growth opportunities $(GO)_{it-p}$ for p ranging from 0 to 4 are proxied by book-to-market ratio (BTM), Tobin's Q (TQ), the ratio of capital expenditure over net value of property, plant, and equipment (Capx), the ratio of long-term debt over equity (Ldebt), and logarithm growth rate of firm-size (Gsize). Those sector-level measures are obtained by averaging each firm-level proxy within each sector. The Global financial crisis dummy, GFC, is equal to one for year 2008 and 2009 and zero otherwise. The European debt crisis dummy, EDC, is equal to one for year 2010 and 2011 and zero otherwise. We also control for macro variables such as logarithm growth rate of GDP (gr_GDP), logarithm growth rate of CPI (gr_CPI), and logarithm of real lending rate (RI). Firm-level control variables are logarithm of firm size (size) and gross profit (gp). Regression results on the four measures of investment opportunities are reported in Panel A, B, C, D, and E, respectively. The sample period is from January of 2006 to December of 2014. Robust t-stats are reported in brackets. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel C: Regressions on capital expenditure						Panel D: Regressions on long-term debt ratio					
Model	-1	-2	-3	-4	-5	Model	-1	-2	-3	-4	-5
Dept Var	ρ	ρ	ρ	ρ	ρ	Dept Var	ρ	ρ	ρ	ρ	ρ
Capx0	0.001**					Ldebt0	0.016*				
	[2.345]						[1.952]				
Capx-1		0.002***				Ldebt-1		0.013			
		[8.087]						[1.277]			
Capx-2			0.002***			Ldebt-2			0.023***		
			[5.029]						[4.018]		
Capx-3				0.001**		Ldebt-3				0.019**	
				[2.383]						[2.371]	
Capx-4					0	Ldebt-4					0.011
					[-0.599]						[1.629]
GFC	-0.004	-0.004	-0.004	-0.003	-0.003	GFC	-0.005	-0.004	-0.005	-0.004	-0.004
	[-0.587]	[-0.528]	[-0.544]	[-0.502]	[-0.531]		[-0.698]	[-0.627]	[-0.689]	[-0.630]	[-0.554]
EDC	0.044***	0.043***	0.044***	0.045***	0.044***	EDC	0.043***	0.044***	0.043***	0.043***	0.044***
	[6.260]	[6.203]	[6.443]	[6.125]	[6.011]		[5.690]	[5.784]	[6.058]	[6.191]	[5.935]
gr_GDP	0.489**	0.514**	0.487**	0.503**	0.495**	gr_GDP	0.449*	0.459**	0.418*	0.463**	0.484**
	[2.470]	[2.797]	[2.685]	[2.819]	[2.851]		[2.155]	[2.345]	[2.079]	[2.390]	[2.681]
gr_CPI	-4.450***	-4.629***	-4.594***	-4.537***	-4.482***	gr_CPI	-4.406***	-4.473***	-4.453***	-4.542***	-4.516***
	[-5.556]	[-5.690]	[-5.673]	[-5.414]	[-5.253]		[-5.517]	[-5.512]	[-5.539]	[-5.523]	[-5.327]
RI	-4.562***	-4.787***	-4.758***	-4.676***	-4.607***	RI	-4.547***	-4.618***	-4.603***	-4.690***	-4.643***
	[-4.325]	[-4.433]	[-4.422]	[-4.239]	[-4.144]		[-4.297]	[-4.267]	[-4.276]	[-4.289]	[-4.190]
size	-0.005	-0.004	-0.007	-0.004	-0.004	size	-0.009	-0.008	-0.014	-0.01	-0.007
	[-0.182]	[-0.155]	[-0.276]	[-0.156]	[-0.143]		[-0.330]	[-0.329]	[-0.528]	[-0.364]	[-0.271]
gp	0.010***	-0.006	-0.002	-0.003	0.001	gp	0.010***	-0.006	-0.001	-0.003	0.001
	[4.320]	[-1.174]	[-0.374]	[-0.653]	[0.208]		[4.462]	[-1.144]	[-0.327]	[-0.636]	[0.346]
Constant	0.338	0.344	0.367	0.339	0.333	Constant	0.369	0.373	0.417	0.386	0.361
	[1.286]	[1.351]	[1.444]	[1.343]	[1.338]		[1.360]	[1.415]	[1.527]	[1.404]	[1.369]
Obs.	440	440	440	440	440	Obs.	440	440	440	440	440
Number of industries	11	11	11	11	11	Number of industries	11	11	11	11	11
Adj.R^2	0.458	0.454	0.452	0.448	0.446	Adj.R^2	0.461	0.451	0.454	0.452	0.448
Industry FE	YES	YES	YES	YES	YES	Industry FE	YES	YES	YES	YES	YES

Panel E: Regressions on growth rate of firm size

Model	-1	-2	-3	-4	-5
Dept Var	ρ	ρ	ρ	ρ	ρ
Gsize0	**0.152***** **[3.246]**				
Gsize-1		**0.218**** **[3.162]**			
Gsize-2			0.089 [1.240]		
Gsize-3				**0.081**** **[2.484]**	
Gsize-4					-0.039 [-0.842]
GFC	-0.005 [-0.710]	-0.005 [-0.802]	-0.004 [-0.667]	-0.004 [-0.607]	-0.003 [-0.475]
EDC	0.042*** [6.176]	0.043*** [6.288]	0.045*** [6.328]	0.045*** [6.099]	0.045*** [6.027]
gr_GDP	0.448** [2.233]	0.448* [2.214]	0.457** [2.424]	0.507** [2.780]	0.490** [2.800]
gr_CPI	-4.635*** [-5.857]	-4.618*** [-5.855]	-4.446*** [-5.517]	-4.512*** [-5.397]	-4.486*** [-5.261]
RI	-4.817*** [-4.659]	-4.724*** [-4.563]	-4.529*** [-4.218]	-4.603*** [-4.169]	-4.625*** [-4.168]
size	-0.009 [-0.335]	-0.01 [-0.373]	-0.009 [-0.349]	-0.004 [-0.180]	-0.003 [-0.134]
gp	0.010*** [4.180]	-0.006 [-1.122]	-0.002 [-0.394]	-0.003 [-0.635]	0.001 [0.218]
Constant	0.385 [1.445]	0.391 [1.450]	0.372 [1.454]	0.338 [1.335]	0.333 [1.340]
Obs.	440	440	440	440	440
Number of industries	11	11	11	11	11
Adj.R^2	0.462	0.458	0.448	0.448	0.447
Industry FE	YES	YES	YES	YES	YES

leads to the lower expected conditional correlation and larger book-to-market leads to the opposite. Therefore, the positive statistical significance of the book-to-market variable implies that the Chinese sectors concern their survival in terms of a reflection of the ability of managers to grow the firm and make corporate investment decisions. This interpretation is consort with the risk based research, too. The bigger book-to-market is associated with the higher distress risk leading to the higher conditional correlation. The higher conditional correlation usually coincides with financial distress or business recession commanding the higher expected returns.

Other panels exhibit consistent results, too. Panel B shows that contemporaneous Tobins Q is significantly positively associated with correlations, although the coefficients on lagged Tobins Qs are not significant. Panel C shows that contemporaneous and lagged capital expenditure variables are strongly positively associated with correlations. The long-term debt ratios and growth rate of size are also significantly correlated with correlations, as observed in Panel D and E. The findings are robust and imply that sector-level correlations with outside shocks capture information about growth opportunities as argued in the previous sections. In addition, the European crisis dummy and macroeconomic variables are significantly and positively correlated to conditional correlations, while the global financial crisis dummy shows no impact on sector-level correlations as shown in all panels of the Table 4. Therefore, our hypotheses are verified.

1.6 Conclusions

We investigated the dynamic conditional correlations between the Chinese sector returns and the S&P500 index. We treated the unexpected changes in the S&P 500 index as an outside shock to the Chinese sectors, and examined how the Chinese sectors respond to the shocks. Using a sample of 12 Chinese sector-level indices, we found that the conditional correlations vary across sectors and across crises. We have verified that conditional correlations of all sectors decreased during the two crises. Moreover, when we associated sector-level correlations with sector-level investment opportunities, we found that the difference in the magnitude of correlations resided in the difference in sector-level growth opportunities. Specifically, the sectors with better growth opportunities and making more investments exhibit higher correlations with the S&P 500 index. This study is meaningful in that we take a first step to examine the economic meaning of the sector-level conditional correlations in the Chinese stock market. Furthermore, our findings contribute to the existing literature by figuring out what micro-determinants drive co-movement among the sector-level correlations and by explaining the conditional correlations dynamics based on investment shocks and corporate investment activities.

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