Leverage Risk and Shadow Banks: Intermediary Asset Pricing in China

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Abstract

We examine how trust companies in China channel the less regulated and run-prone funds to the capital market and how these shadow banking activities amplify investment leverage. We find that leverage risk factors constructed from trust companies can explain both time series and cross-sectional asset returns. Our results support the leverage-based CAPM model predictions and complement the intermediary asset pricing theory: the intermediaries are marginal investors who determine the state price of density. The trust leverage factors are not only statistically but also economically significant. In contrast, the leverage derived from the securities companies possesses no power in explaining asset returns in a broad set of asset classes, though these companies are the legitimate financing sources of leveraged investment. This stark contrast reveals unintended consequences of strict funding regulation, giving rising to rampant leverage in investment. Specifically, leverage risks are concentrated in the stock market through prosperous lending vehicles such as umbrella and mezzanine trusts.

JEL Codes: G01, G10, G20
Key words: leverage constraint, shadow banking, leverage risk factor, intermediary asset pricing

1 Introduction

The intermediary asset pricing theory (see He and Krishnamurthy (2012, 2013), and Brunnermeier and Sannikov (2014)) asserts that the marginal utility of every dollar financed by

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intermediaries, rather than that of every dollar consumed by households, determines the state price density and hence the asset price. He, Kelly, and Manela (henceforth HKM) and Adrian, Etula, and Muir (henceforth AEM) find that the broker-dealer leverage possesses significant explanatory power in time series and cross-sectional asset returns in the U.S. market. The success of these empirical analysis relies on temporal variation in leverage (Geanakoplos (2010)). Much less on leverage risks has been done in the immature markets because either people generally agree that the low intermediary leverage in these markets presents little risk variation in contrast to that in developed markets or it is challenging to derive an empriical leverage factor due to data availability. Acharya et al. (2013) show that an expansion of shadow banking activities causes soaring leverage in India and Acharya et al. (2016) that the Chinese commercial banks become financially fragile when these banks work with shadow banks and issue short-lived wealth management products (WMPs). The latest 2005 stock market crash in China has drawn regulatory scrutiny on managing leverage. Our paper examines asset price and intermediary leverage risk in Chinese market. It shed light on quantifying the rampant leverage risk arising from shadow banks and complements the intermediary asset pricing theory prevailing in the U.S. market.

Our first and key contribution is that, by comparing the trust leverage factors with the security leverage factor in two samples, shadow banking activities[1] create unregulated funds and lead to unprecedented *investment* leverage risks that are beyond China regulators foresee. In a full sample of stocks, bonds, and all asset, the prices of risk regressed against the security leverage factor are statistically insignificant. In the subsample of pooled stocks for

[1]Pozsar et al. (2010) define shadow banks as financial intermediaries that conduct maturity, credit, and liquidity transformations without explicit access to central bank liquidity or public sector credit guarantees; Ghosh et al. (2012) define shadow banking as comprising a set of activities, markets, contracts, and institutions that operate partially (or fully) outside the traditional commercial banking sector and as such are either lightly regulated or not regulated at all. The distinguishing feature of shadow banking is that it decomposes the process of credit intermediation into a sequence of discrete operations.

which transaction securities companies are the unique financing sources, the leverage factor can explain the cross-sectional returns. However, they become insignificant once we include the trust leverage factor. This comparison has two implications. Firstly, from the securities companies' point of view, these companies are the licensed entities for financing leveraged investments in the selected stocks, and their leverage reflects the funding conditions of these stocks. Innovations to securities company leverage measure the securities companies' capital scarcity and hence conveys information explaining the stock returns in the subsample. However, due to restricted lending of the securities companies, these innovations do not have sufficient temporal variation. Therefore, the securities companies have limited power in the subsample and completely lose their explanatory power in the full sample since these companies do not finance the transaction of securities. Secondly, from the trust companies' point of view, these companies create massive off-balance sheet funds that investors can borrow to lever up trading. This generates great variations in innovations in the trust company leverage because trust companies are information-sensitive in lending. The comparison confirms that the trust leverage factors dominate the security leverage factor in terms of statistical significance and economic magnitude of the prices of risk. The difference indicates that leverage risk has become excessive in China and arisen from shadow banks: the trust companies. The difference also reveals that strict funding regulation has unintended consequences that banks exploit regulatory arbitrage as much as possible, giving rise to the prosperity of the shadow banking and excessive leverage risks.

Specifically, we elaborate the second implication by calibrating the leverage amplification multiplier. The higher the multiplier is, the higher the leverage is. We set the risk distortion term to the value that compensates leverage risk on average. We calibrate the parameters using market data and find that this number decreases in the stocks, bonds and for the whole market, in that order, and increases at the maximum loss that monitors leverage. The pattern reveals the shadow banking activities hence the leverage risks are concentrated in the shock market as most special vehicles are created to finance stock trading prior to the 2005 equity market crash. Without account-based trade data, it is very difficult to know exactly how the leverage arising from the shadow banks exists is in the asset market in China. Our calibration provides a way to back out this multiplier as soon as the prices of the risk of the leverage factor are attained.

Our second contribution is that this work complements intermediary asset pricing theory in several dimensions. In an emerging market, absent sophisticated financial instruments, leveraged bets cannot be excessive because borrowing from banks to invest is prohibited and borrowing from broker-dealers is limited. We details how banks and trust companies work together in the appendix to transfer WMP funds into trust funds, of which a large fraction were pumped into the stock and bond markets prior to the 2015 stock market crash. We define such bank-trust cooperation as a kind of shadow banking activity. This activity features unregulated funds that encourage leveraged investments for risk-tolerant investors who are unable to borrow from other sources. We build a leverage-based CAMP reflecting the leverage risks in such a process. Our model captures capital flow from households to intermediaries, including banks and trust companies, to investors, take into account leverage magnification, and connect the leverage risk with the asset price. Our model directs us to a two-factor asset pricing model that facilitates empirical study.

Furthermore, we identify the empirical leverage factors. We exploit two intermediaries: securities companies, which are broker-dealer counterparties in China, and trust companies, which represent shadow banks. Securities companies are the privileged intermediaries from which investors borrow through short-selling and the margin trading of pooled stocks. No entity other than securities companies can conduct such activities in compliance with regulation. However, investors can only lever up to a limited amount, and the borrowing must be booked in the balance sheets of the securities companies. In contrast, trust companies can provide massive unregulated WMP funds to finance securities transactions, giving rising to much higher investment leverage. Specifically, we differentiate the trust asset under management (AUM) in the stock market from the that in the bond market. By doing so, we obtain three market-specific leverage risk factors for trust companies. We employ the asset-to-equity ratio to define the leverage ratio. The asset term corresponds to the trust AUM in the stock market, the trust AUM in the bond market, and the total trust AUM in the whole capital market. We imply the three leverage factors: the trust stock leverage factor, the trust bond leverage factor, and the trust aggregate leverage factor. We will give the rationale that the market-specific leverage factor is appropriate and necessary in China.

Our three leverage factors possess explanatory power in the cross-section and time series for both the stock and bond returns. We sort and form three portfolios representing three asset classes: stocks, bonds, and all assets. We run the cross-sectional regressions of asset returns against the market-specific leverage factors. We find that prices of risk regressed against the three trust leverage factors are statistically significant cross-sectionally in the three asset classes. In order to investigate the magnitude of the prices of risk, we obtain the return-based leverage factors by projecting the non-traded leverage factors to the leverage-based factors, mimicking portfolio returns. Running the same cross-section regressions against the return-based leverage factors, we find that the prices of risk against the return-based leverage factors are economically significant as well, and the values are 28% p.a. for the return-based trust stock leverage factor in stocks; 12% p.a. for the return-based trust bond leverage factor in bonds; 8% p.a. for the return-based aggregate leverage factor in all assets. Specifically, the prices of risk on the trust stock leverage factor in stocks are evidently larger than those on the trust bond leverage factor in bonds. The trust aggregate leverage factor exhibits prices of risk in stocks that are also higher than the counterparts in bonds. Such a difference is not surprising as extensive leverage risks are present in the equity market. We witnessed an unprecedented deleveraging campaign in July 2015 in China's equity market that cut off unregulated financing from shadow banks. The intermediary asset pricing theory predicts that leverage risk is best priced at the bottom of the leverage cycle where the dollar is most valuable for trust companies. In the time series regression, the three trust leverage factors strongly predict returns in the three assets as well. We conclude that our work complements the recently developed asset pricing theory in emerging markets where trust companies are marginal investors, which is tested in mature financial markets such as the U.S. market by He et al. (2016) and Adrian et al. (2014) where broker-dealers are marginal investors..

We conduct several robustness checks on our results. First, we explore a comprehensive race between factors as much as possible. Our trust leverage factors survive the race versus a set of commonly used asset pricing factors, such as the Fama-French three factor model, the Fama-French five factor model, the momentum factor, Pastor-Stambaugh liquidity factor, and combinations thereof. Second, our results hold in a longer series to cope with our small sample size at a quarterly frequency. We can certainly verify our results using the monthly return-based leverage factors in the spirit of AEM. However, we justify this approach with a much more direct method: We collect the daily trust plans released by trust companies and aggregate the monthly trust AUM. We then derive a monthly trust aggregate leverage factor since every trust plan reports its fund size but no asset class that it invests in. The cross-sectional regression results are consistent with those of the regression on the quarterly series except for the fact that the prices of risk are smaller in magnitude.

Related Literature

Our paper resides within intermediary asset pricing theory, which elevates financial intermediaries to the marginal pricer of asset values. Early contributions to this theory include Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). In the aftermath of the financial crisis, there is a growing literature about dynamic asset pricing models that take into account intermediary constraints. The recent burgeoning theoretical work includes Brunnermeier and Pedersen (2009), Geanakoplos (2010), Adrian and Shin (2014), He and Krishnamurthy (2012, 2013), and Brunnermeier and Sannikov (2014). Empirical findings on this subject have accumulated recently and include those of AEM, HKM, Chen, Joslin, and Ni (2016), and Adrian et al. (2013). Our paper is mostly relevant to the works of AEM and HKM, who empirically justify intermediaries determining the marginal value of one dollar instead of households. AEM uses the broker-dealer book leverage to explain cross-section asset returns in the U.S. equity and bond markets. Our leverage ratio is similar to that defined in AEM. HKM studies seven asset classes cross-sectionally using the market equity ratio derived from the holding companies of the prime dealers in U.S. The results from HKM are significant and robust for the U.S. data. HKM in particular carefully compare their equity ratio factor with the AEM leverage factor. HKM argue that the AEM leverage factor is more powerful in stocks and bonds and that its power is weakened outside stocks and bonds. We do not intend to pursue which factor is a more accurate proxy for the empirical pricing kernel of intermediaries; rather, we aim to complement the empirical evidence from HKM on intermediary asset pricing beyond the U.S. market, and we are successful in this regard. We do show that trust companies in China as the main bodies of shadow banks are marginal over households in determining asset values. More importantly, our results estimate the effect of leverage risks arising from the shadow banking on asset prices. We argue that leveraged bets in the usage of shadow funds are one of the major reasons for the equity rally and crash after 2010 in China. Our paper is also relevant to the forecasting power of intermediary leverage factors. Adrian et al. (2013) show that broker-dealer leverage has significant time-series power in forecasting returns on stocks and bonds. Chen, Joslin, and Ni (2016) connect the trading quantities of deep out-of-money options with the tightness of intermediary constraints and show that such quantities are associated with high risk premia for a wide range of financial assets.

Our paper is also close to a growing body of research on shadow banking and financial fragility in India and China. (Acharya et al., 2013) study the determinants of the expansion of shadow banking in India. Leverage risks in shadow banking in China have been addressed from different angles. Hachem and Song (2016) show that shadow banking activities evading liquidity regulations in China drive up the interbank interest rates. Acharya et al. (2016) examine the relationship between the off-balance sheet WMPs and the issuing banks in China and find that shadow banking activities, which are notable for the issuance of WMPs, have contributed to a greater fragility of the banking system. Chen, Ren, and Zha (2016) link the shadow banking activities with entrusted loans from commercial banks. The authors argue that the loan-to-debt ratio regulation, coupled with other regulations, creates an incentive for small banks to bring the risk from shadow loans into their balance sheets through regulatory arbitrage. Chen, He, and Liu (2017) document the relationship between China's four-trillion-yuan stimulus package in 2009 and shadow banking activities, including entrusted loan and WMPS, after 2012. Our paper takes a different perspective by linking credit transfer and leverage amplification in shadow banking with asset pricing both theoretically and empirically. Specifically, we build a leveraged-based asset pricing model to motivate the empirical asset pricing model tests.

The remainder of the paper is structured as follows. We build a leveraged-based asset pricing model featuring a trade-off between intermediary leverage magnification and leverage risk monitoring in Section 2. Section 3 contains our dataset and constructs the leverage factors and asset returns. We provide our main empirical results, which show that trust companies as intermediaries in China are marginal investors, in Section 4. We provide robustness checks in Section 5 and conclude in Section 6.

2 Leveraged-Based CAPM

We build a stylized leveraged-based CAPM that characterizes asset returns and leverage amplification in the shadow banking activities: the umbrella trusts and the mezzanine trusts. The shadow banking activities are detailed in the Appendix. They are popular two popular tools that transform credit and magnify leverage magnification in the capital market. We study the most popular umbrella trusts and give mezzanine trusts in the Appendix. Our leveraged-based CAMP model motivates us to empirically test a regression asset pricing model in which the leverage derived from trust companies services as a risk factor.

2.1 Asset Market

Consider a pure-exchange economy with a single consumption good. The uncertainty is represented by a filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}, \mathcal{P})$ in which a one-dimensional Wiener process is defined. The securities market trades a risky asset with a net supply of one unit, a risk-free bond in zero net supply, and a risky WMP in zero net supply. The risky asset is a claim to an aggregate dividend denoted by D_t per unit of time. The risky asset and bond prices are S_t and B_t in equilibrium, respectively. The total return on the risky asset is $dR_t = \frac{D_t dt + dS_t}{S_t}$ with the constant expected growth rate μ and constant volatility σ. The WMP is a claim to aggregate dividends as well and earns a stochastic return $\tilde{R}$, to be specified later. It will become clear that the WMP in our setup is redundant.

2.2 Agents

There are three classes of agents: households, investors and fund-matching companies. Households invest in bonds and WMPs to maximize their expected discounted utility

$$\mathbb{E}\Big[\int_0^\infty e^{-\rho_h t} u(c_{h,t}) dt\Big] \tag{2.1}$$

subject to

$$dW_{h,t} = W_{h,t}\big[r_t dt + \alpha_{h,t}(d\tilde{R}_t - r_t dt)\big] - c_{h,t} dt, \tag{2.2}$$

where $\alpha_{h,t}$ is the ratio of the risky WMP holding of households to their total wealth and $c_{h,t}$ is their consumption. Households do not invest in the risky asset due to a lack of expertise. Households indirectly participate in the risky asset market through the structural WMPs. Investors can only borrow from fund-matching companies to trade the risky asset[2]. The rationale for this dynamic is that that market frictions such as constraints and regulations prohibit investors from borrowing directly from households (see, e.g., He and Krishnamurthy (2013) for more about market frictions limiting participation). Specifically, the unsophisticated financial market in emerging markets like China makes it difficult or even impossible for investors to access the regulated credit market. The main financing sources for investors are the less regulated shadow banks.

The key ingredient of our model is given by fund-matching companies. Fund-matching companies borrow the WMP funds from households; however, these companies lend to investors. In doing so, fund-matching companies must offer a higher return on the return from investors. In other words, fund-matching companies negotiate with investors as to how much

[2]We can allow investors to borrow a limited number of bonds; however, this restriction does not yield new insights.

they benefit from their investment in the risky asset when lending capital[3]. We assume that borrowing and lending between fund-matching companies and households are costless to simplify the argument and characterize the rule of profit division between fund-matching companies and investors as in He and Milbradt (2014).

Suppose the wealth of fund-matching companies on date t is $W_{s,t}$. The companies borrow up to $\alpha_t W_{s,t}$ against their wealth by subscribing to the junior tranche in one WMP. We assume $\alpha_t > 1$. As long as they raise $\alpha_t W_{s,t}$, the fund-matching companies open multiple sub-accounts under an umbrella trust, allocate $\alpha_t W_{s,t}$ evenly to each sub-account, and allow investors to use these accounts to trade the risky asset in the spirit of Figure 7. Specifically, each investor promises a return $\tilde{R}_t$ and hands the same amount of upfront cash to the fund-matching companies so that the total upfront cash handed back to the fund-matching companies is as much as $W_{s,t}$. Fund-matching companies can keep repeating the fund matching scheme n times and end up with leverage reaching up to $n\alpha_t$. Observe that each investor identically leverages up to α_t. Each investors maximizes the expected discounted utility

$$\mathbb{E}\Big[\int_0^\infty e^{-\rho t}\ln(c_{i,t})dt\Big] \tag{2.3}$$

subject to

$$dW_{i,t} = W_{i,t}\big[d\tilde{R}_t + \alpha_{i,t}(dR_t - d\tilde{R}_t)\big] - c_{i,t}dt, \tag{2.4}$$

where $\alpha_{i,t}$ is the ratio of the risky asset holding to the total wealth and $c_{i,t}$ is the consumption

[3] We essentially isolate the failure in which fund-matching companies cannot deliver the promised WMP return to households and concentrate on the relationship of these companies to investors. Admittedly, it would be meaningful approach to study the failure to deliver WMP returns and financial fragility (seeAcharya et al. (2016)).

for investors. In contrast, fund-matching companies maximize the expected wealth growth[4]

$$\mathbb{E}\Big[\int_0^\infty e^{-\rho t}\frac{dW_t^s}{W_t^s}\Big] \tag{2.5}$$

subject to

$$dW_{s,t} = W_{s,t}\big[r_t d + n\alpha_t(d\tilde{R}_t - r_t dt)\big]. \tag{2.6}$$

Additionally, fund-matching companies implement two policies to monitor risk. The first is a VaR constraint reflecting the aggregate risk appetites over the potential losses

$$\mathrm{Var}_t\Big(\frac{dW_{s,t}}{W_{s,t}}\Big) \leq \bar{\sigma}^2 dt, \tag{2.7}$$

where $\bar{\sigma}$ represents the volatility as a measurement of the maximum investment loss. The second corresponds to the risk control on each sub-account reflecting that fund-matching companies would require each investor on average to lever up not beyond what they can lever up in every WMP α_t

$$\alpha_{i,t} \leq \alpha_t. \tag{2.8}$$

Another feature of our model is that fund-matching companies indirectly participate in the risky asset market on behalf of households and grab a fractional profit, ν, from investment in the risky asset through the following division rule (see also He and Milbradt (2014))

$$d\tilde{R}_t - rdt = \nu_t(dR_t - d\tilde{R}_t), \tag{2.9}$$

with $0 < \nu_t < 1$. Rule (2.9) is equivalent to

$$d\tilde{R}_t - rdt = \omega_t(dR_t - rdt), \tag{2.10}$$

[4]We assume that fund-matching companies are risk neutral.

with $\omega_t = \frac{\nu_t}{1+\nu_t}$, representing a fractional profit of fund-matching companies in term of the excess return of the risky asset. We assume that lending between households and fund-matching companies is frictionlessly and leave it for the sake of simplicity. The profit division rule can be relaxed, but this feature captures the critical lending friction in shadow banking, which impairs perfect risk sharing once combined with constraints.

We now solve the leverage-based CAPM model with the help of the profit division rule (2.10) and the techniques used in other works, e.g., Ashcraft et al. (2010) and Chabakauri (2013). The log preference immediately implies that the consumption processes of investors are proportional to their wealth with rate ρ and that the Hamilton-Jacobi-Bellman (HJB) equation of investors reduces to the myopic mean-variance maximization for investors

$$\max_{\alpha_{i,t}}[(\omega_t + (1-\omega_t)\alpha_{i,t})(\mu_t - r_t) + r_t] - \frac{1}{2}(\omega_t + (1-\omega_t)\alpha_{i,t})^2\sigma_t^2 \tag{2.11}$$

subject to (2.8), and for fund-matching companies

$$\max_{\alpha_t}[n\omega_t\alpha_t(\mu_t - r_t) + r_t] \tag{2.12}$$

subject to

$$(n\omega_t\alpha_t)^2\sigma_t^2 \leq \bar{\sigma}^2. \tag{2.13}$$

We make an important assumption

$$\mu_t - r_t > 0,$$

under which fund-matching companies take the maximal leverage in such a way that their risk exposures do not exceed their tolerated limit

$$\alpha_t = \frac{\bar{\sigma}}{n\omega_t\sigma_t}. \tag{2.14}$$

Individual investor leverage constraint (2.8), which satisfies

$$\alpha_{i,t} \leq \frac{\bar{\sigma}}{n\omega_t\sigma_t}. \tag{2.15}$$

If we denote the shadow cost of the leverage constraint of investors (2.15) by ϕ_t, we can derive the leveraged CCAPM for the problem (2.11) of investors

$$\mu_t - r_t = \mathrm{Cov}_t\Big(\frac{dC}{C}, \frac{dS}{S}\Big) + y_t\frac{n\omega_t\sigma_t}{\bar{\sigma}}\phi_t, \tag{2.16}$$

where y is the relative consumption share of investors to households $\frac{c_i}{c_h+c_i}$. Given the exogenous consumption process and the optimal risky asset holding of investors[5], we can pin down the equilibrium prices, but we we do not pursue these figures here. Supposing the market portfolio W return has the highest possible (instantaneous) correlation with the aggregate consumption growth, and using

$$\beta_{R,t} = \frac{\mathrm{Cov}_t\Big(\frac{dW}{W}, \frac{dS}{S}\Big)}{\mathrm{Cov}_t\Big(\frac{dW}{W}\Big)},$$

we can write the leveraged CCAPM in terms of a market portfolio in place of the aggregate consumption as

$$\mu_t - r_t = \beta_{R,t}\lambda_{W,t} + y_t\frac{n\omega_t\sigma_t}{\bar{\sigma}}\phi_t, \tag{2.17}$$

where $\lambda_{W,t}$ is the price premium of the market portfolio. This model is the leverage-based CAPM with the same structure as the margin-based CAPM in Garleanu and Pedersen (2011).

[5]The optimal risky asset holding of investors is

$$\alpha_{i,t} = \begin{cases} \Big(\frac{\mu_t - r_t}{\sigma_t^2} - \omega_t\Big)\frac{1}{1-\omega_t}, & \Big(\frac{\mu_t - r_t}{\sigma_t^2} - \omega_t\Big)\frac{1}{1-\omega_t} \leq \frac{\bar{\sigma}}{n\omega_t\sigma_t} \\ \frac{\bar{\sigma}}{n\omega_t\sigma_t}, & \text{otherwise.} \end{cases}$$

Observe that the lending friction ω and the leverage constraint $\frac{\bar{\sigma}}{n\omega_t\sigma_t}$ impair perfect risk sharing and prevent investors from holding the first best $\frac{\mu_t - r_t}{\sigma_t^2}$.

Specifically, the expected return of the risky asset in our leverage-based model is determined by the product of the market beta and market risk premium as well as a distortion term due to fund-matching companies monitoring leverage risk. The distortion reflects the relative importance of investors y, the bargaining power between investors and fund-matching companies ω, the leverage constraint on investors from fund-matching companies $\frac{n}{\bar{\sigma}}$, and the risky asset volatility σ. The distortion term is not a product of the leverage beta and the leverage risk premium and is thus not a leverage risk factor model. Therefore, we are not able to use this term to test the leverage risk directly. However, this restirction has interesting implications that motivate us to gauge leverage as a risk factor. Note that from $\alpha_{i,t} = \frac{\bar{\sigma}}{n\omega_t\sigma_t}$, the leverage of investors is forced to be low in bad states because the risky asset volatility σ tends to be high, suggesting a negative relation between the risky asset volatility and the leverage. If the constraint expressed by $\frac{n}{\bar{\sigma}}$ is allowed to be time varying and stochastic, there must exist covariation between the risky asset volatility and the leverage. We make a bold conjecture that the distortion term is approximated by the risky asset exposure to leverage risk and the leverage risk premium. Namely, our leverage-based CAMP is approximated by a linear two-factor asset pricing model

$$\mu_t - r_t = \beta_{R,t}\lambda_{W,t} + \beta_{LevFac,t}\lambda_{LevFac,t} \tag{2.18}$$

where $\beta_{LevFac,t}$ and $\lambda_{LevFac,t}$ are the risk loading on and the risk premium of the leverage risk factor, respectively. In this regard, AEM surely do a better job indicating that the net wealth of the intermediaries is a fraction of the household wealth. The authors use an exogenous process for this fraction and derive a two-factor asset pricing model. We choose to take an exogenous constraint approach that we believe better demonstrates the connection between asset prices and leverage risks from shadow banking activities. In the end, we test leverage risks by applying a two-factor model to the data and answer the following questions: 1. Are leverage risks priced? 2. Is the economic magnitude of leverage risk sizable? 3. Is the exposure to leverage risk truly connected with shadow banking activities?

3 Data

Section A shows how investors borrow "shadow" money and lever up to invest in the risky asset market through bank-trust cooperation. Chinese banks are heavily regulated, and they market WMPs more than they invest in WMP funds. The leverage of these banks is not an appropriate risk factor. Fund-matching companies are the best representatives of the shadow banks, as described above, in amplifying leverage. These companies are not regulated in nature, and their leverage cannot be obtainable, otherwise it would be too good. The "channel" trust companies are less regulated compared with banks and securities companies. These companies can produce much higher leverage by borrowing enormous amounts of WMP funds and lending with less regulation. Therefore, we take the leverage of the trust companies as our leverage risk factor in (2.18). We separate securities companies from trust companies for the reason to be shown in the empirical tests.

3.1 Leverage Risk Factors

Data about trust companies come from two sources: quarterly balance sheet data provided by the China Trustee Association and hand-collected trust plans from China's biggest online financial service website, eastmoney.com. The China Trustee Association releases quarterly reports on the aggregate balance sheets in the trust industry comprising 68 trust companies from 2010. Specifically, these reports detail the trust AUM categorized by asset class: stocks, bonds, and non-financial assets. We exclude the non-financial AUM and calculate the aggregate trust leverage as

$$\frac{\text{trust AUM in stock and bond + total equity}}{\text{total equity}}$$

in each quarter. The change in this trust leverage measures the net flow into the capital market and hence the funding liquidity that trust companies provide. Analogously, we define the trust stock leverage and trust bond leverage as follows:

$$\frac{\text{trust AUM in stock + total equity}}{\text{total equity}},$$

$$\frac{\text{trust AUM in bond + total equity}}{\text{total equity}},$$

respectively. We will explain why we consider the market-specific leverage factors for trust companies rather the uniform factor as in AEM and HKM. We also calculate the leverage of securities companies using data from the quarterly financial reports for a total of 26 listed securities companies from the Wind database. These listed securities companies control the majority of brokerages in China. The quarterly sample is for the period 2010Q1-2016Q2.

Unfortunately, our quarterly series is relatively short, and we have a small sample size. In order to make the results robust, we obtain a longer time series sampled at a higher frequency. We employ a web crawler to collect the publicly announced trust plans from the Eastmoney website (www.eastmoney.com). We collect every trust fund plan, including the trust fund ID, start date, end date, fund size, and plan type, each day. We aggregate the daily AUM of every trust plan across all trust companies to obtain the monthly trust AUM in the capital market. The publicly announced trust plan classifies assets as financial or non-financial assets, meaning that we can only have one trust leverage value per month for the monthly series. We hold the quarterly trust total equity unchanged within one quarter and calculate the monthly leverage of trust companies as

$$\frac{\text{trust AUM in capital market + total equity}}{\text{total equity}}$$

in each month. The monthly leverage calculated from the online data is just an approximation of the real monthly leverage because trust companies do not post all trust fund plans.

Finally, we produce four leverage ratios: one for securities companies and three for trust companies. Because leverage is calculated in terms of the book value, we run an AR(1) regression on each leverage to eliminate persistence and keep innovation in each regression. We then define the leverage factor by normalizing innovation by the one-period lagged leverage. Through this process, the four leverage series produce four leverage risk factor series from 2010Q2 to 2016Q2: the securities company leverage factor, denoted by LevFac-S; the trust aggregate leverage factor derived from the trust AUM in both the stock and bond markets, denoted by LevFac-TA; the trust stock leverage factor derived from the trust AUM in the stock market, denoted by LevFac-TS; and the trust bond leverage factor derived from the trust AUM in the bond market, denoted by LevFac-TB.

We provide the descriptive statistics on size, leverage, and leverage factors of the trust and listed securities companies in Table 1. Panel A in Table 1 summarizes the assets managed by the trusts and listed securities companies in China. From 2010 to 2016, the quarterly trust AUM in the financial market reached 1,196 trillion RMB on average, which accounts for one-half of the asset of the securities companies and 7% of the GDP of China, which is huge. Of the funds channeled into the asset market through trust companies, 40% are in the stock market[6] and 60% are in the bond market. Assets managed by the 26 listed securities companies account for 75% of the total assets from all 125 of the securities companies in China per the annual report of the China Security Association. One interesting note, not shown in the table, is that the trust leverage is 7.23 on average, which is much higher than the security leverage of 2.81. Panels B and C in Table 1 present the pairwise correlations between the trust and security leverages and their factors. The levels of all the defined leverage values are highly correlated. The trust aggregate leverage factor is more correlated with the stock leverage factor of 0.77 than with the bond leverage factor of 0.31. Notably, the stock

[6]Funds in China are baskets of stocks.

leverage factor is negatively correlated with the bond leverage factor with a correlation of -0.35. This finding implies a considerable asset substitution between the stock market and bond market in China, which is why we separate the trust stock leverage from the trust bond leverage. Additionally, the correlation between the security leverage and the trust aggregate leverage is 0.62 but drops to 0.14 between the security leverage factor and the trust aggregate leverage factor. The correlation between the security leverage factor and the trust stock leverage factor is only 0.02, which indicates that the security leverage is unlikely to be an appropriate risk factor for explaining asset returns if the trust stock leverage factor can do so.

It is worth speaking of the monthly trust aggregate leverage derived from the online data. First, the trust AUM aggregated from the online data is on average 584 billion RMB, as shown in Panel A, Table 1. We aggregate the quarterly online trust AUM from the monthly online data then divide these values by the true quarterly trust AUM. The ratio has a mean of 0.49 and a standard deviation 0.03. The aggregated value is reasonably comparable to the true value. Second, the median, maximum and minimum of the online trust aggregate leverage factor are calculated, and these figures maintain a constant proportion to those of the true trust aggregate leverage factor. This result shows that both leverage factors exhibit similar variations. Third, Panel A and Panel B in Table 1 show that the correlation between the online trust leverage, which is aggregated into quarterly values and is denoted by Lev-TA(q), and the true leverage is 0.99 and is 0.85 between the online trust leverage factor, which aggregated into quarterly values and is denoted by LevFac-TA(q), and the true leverage factor. These correlations indicate that the monthly trust leverage factor derived from online data is a good proxy for the true monthly trust leverage factor, and the results give us confidence in using this larger subsample of the longer factor series.

[Table 1 about here.]

3.2 Test Assets

The asset data are from the Wind database. We have three asset classes: stocks, bonds, and all assets, which merges stocks and bonds. We do not consider derivatives because only very few derivatives (3 index futures and 1 index option) are traded in China. For stocks, we use the Fama and French (1993) method to sort the stocks traded on the Shanghai and Shenzhen Stock Exchanges into 25 size and value portfolios. For bonds, we have 5 maturity-sorted government bonds with maturities varying from 3 months to 10 years; 20 corporate bond portfolios sorted into 5 yield spreads according to Nozawa (2014) and by 4 maturities. In the end, we merge stock portfolios and bond portfolios to produce the all asset class. Furthermore, we consider a subsample of pooled stocks that are selected for margin trading and short-selling. The size of this subsample has been increasing, and the subsample includes 90 stocks in 2010Q1 and 904 stocks in 2016Q2. We sort this subsample of stocks into 15 portfolios by 3 size portfolios 5 value portfolios. We then calculate equally weighted return time series for analysis.

3.3 Regression Asset Pricing Models

We use the following generic asset pricing regression based on Equation (2.18)

$$R^e_{i_k,t} = a_{i_k} + \beta_{i_k,LevFac} LevFac_t + \beta_{i_k,m} R^e_{m,t} + \beta'_{i_k,t} f_t + \varepsilon_{i_k,t} \tag{3.1}$$

where $R^e_{i_k}$ is asset i_k's return in excess of the risk-free rate from asset class $k \in$ {Stocks, Bonds, All}; $LevFac$ is the leverage risk factor from {LevFac-S, LevFac-TS, LevFac-TB, LevFac-TA}; R^e_m is the market factor that is the stock market portfolio return net the risk-free rate; and f is a vector of other risk factors. In order to estimate the cross-sectional prices of risk for each factor, we run a Fama and MacBeth (1973) cross-sectional regression of the average asset returns, $\mathbb{E}[R^e_{i_k,t}]$, on the risk factor exposure in each asset class k to estimate the asset class-specific prices of risk λ_k and the average asset class-specific pricing error γ_k.

$$\mathbb{E}[R^e_{i_k,t}] = \gamma_k + \hat{\beta}_{i_k,LevFac}\lambda_{k,LevFac} + \hat{\beta}_{i_k,m}\lambda_{k,m} + \hat{\beta}'_{i_k}\lambda_{k,f} + u_{i_k} \tag{3.2}$$

If our choices of trust leverage factors have any chance to explain returns, they should be procyclical, which is imposed by the intermediary asset pricing theory in the framework of the leverage constraints. We illustrate this feature by looking at the trust stock leverage. Our trust stock leverage factor (dashed green) in Figure 1b, for example, does exhibits a strong procyclicality. This factor was low and flat during 2011-2012 but began picking up as soon as the CSI 300 index started to rally in early 2014 and then peaked just as the CSI 300 index did. Since an adverse policy shock arrived as the CSRC attempted to suppress shadow banking lending in the first quarter of 2015, trust companies were forced to unwind their portfolios and deleverage in order to satisfy capital requirements, where the marginal value of every unit of RMB of the trust companies is highest. A lower asset price was needed to clear the market in equilibrium. Consequently, the CSI 300 index dropped, and leverage shrank, after the second quarter of 2015. In other words, the leverage will procyclically impose positive prices of risk on the trust leverage risks. In contrast to that of trust companies, the security leverage in Figure 1a does not feature strong procyclicality. As expected, our empirical results affirmatively justify these observations.

[Figure 1 about here.]

4 Empirical Analysis

We conducted both cross-sectional and time series empirical analyses. In the following cross-sectional regressions, we follow Fama and French (1993) and include the following factors: Market - the stock market factor, which is the equity market portfolio return net 1 year at the risk-free rate; DEF - the credit risk factor, which is the market index return of corporate bonds net 10 years at the government bond return rate; TERM - the bond market factor, which is the 10-year government bond return net 1 year at the risk-free rate. Our trust leverage factors are market-specific in that we use the trust stock leverage factor to explain stock returns, the trust bond leverage factor to explain bond returns, and the trust aggregate leverage factor to explain stocks, bonds, and all asset returns. This approach makes our interpretation challenging, but we reason that it is worth doing so. We refer to a benchmark model whenever a regression includes one leverage factor and the Market, DEF and TERM factor.

4.1 Cross-sectional Analysis

Table 2, 3 and 4 present the main cross-sectional regression results. Table 2 and Table 3 are the factor prices of risk against the trust leverage and the security leverage in stocks, bonds, and all. Table 4 compares the prices of risk regressed against the trust leverage factor with those regressed against the security leverage factor in a subsample of stocks that investors can short-sell and margin trade. We associate the market-specific leverage factor with the asset class in the regressions. Namely, the stock leverage factor is associated with stocks, the bond leverage is associated with bonds, and the aggregate factor is associated with all assets. We also report the prices of risk regressed against the trust aggregate leverage factor in stocks and bonds for comparison. In addition to the FM (Fama and MacBeth (1973)) t-statistics, we report the GMM (Hansen (1982)) t-statistics to correct for the cross-correlation and first-stage estimation error in the betas. We also report the adjusted cross-sectional R^2 and the mean absolute pricing error, or MAPE.

First, we notice that the estimated factor prices of risk are positive and significant when regressed against the three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in three asset classes: stocks, bonds, and all. Specifically, the prices of risk regressed against the corresponding trust leverage factor are significant at levels of either 1% or 5% in the benchmark models (3), (6), (9), (12), and (16). The GMM t-statistics for these prices are 3.42 in Model (3), 3.20 in Model (6), 2.24 in Model (9), 4.25 in Model (12), and 3.71 in Model (16). Note that the prices of risk regressed against the trust leverage factors are significant as well in other models. The statistical significance of the prices of risk against the leverage risk factors is consistent with what has been documented by AEM and HKM in the U.S. Strikingly, the Market - the equity market factor - prices of risk are insignificant in either stocks or all and weakly significant in bond; the TERM - the bond market factor - prices of risk are insignificant in both bonds and all and significant in stocks[7]. When the trust leverage factor is regressed against the asset market, from which the leverage factor is derived, the trust leverage factor can explain the cross-sectional returns significantly in this asset class, but the market factor in the associated asset class cannot. In the language of intermediary asset pricing theory, the intermediaries - trust companies in China - are the marginal investors that determine asset values rather than households. It is quite surprising given that the Chinese financial market is far inferior to the U.S. financial market and the leverage risk is understood low. Second, the benchmark models in each asset class generate R^2 values between 34% and 57% and produce fairly small MAPEs, indicating reasonable goodness of fit in this small sample, which is also consistent with those in the U.S. We will not elaborate on the goodness of fit of the asset pricing model but focus on what the results indicate. In addition, the singe-leverage factor models (1) and (7) with factors LevFac-TS and LevFac-TA have R^2 values of 20% and 24%, respectively, in stocks, outperforming the single-factor model (4) for LevFac-TB in bonds and the-single factor model (10) and (13) for LevFac-TA in bonds and all. The reason for this result is the segmentation between the stock and bond markets in the Chinese market. The flow of funds to the bond market from

[7]The prices of risk for DEF are understandably insignificant in stocks but significant in bonds.

trust companies is almost twice as much as that to the stock market from trust companies. In the Chinese market, the bond market has long exhibited a bullish rally within our sample, but the equity market has experienced more ups and downs in our sample. The trust stock leverage and bond leverage are different and behave differently in pricing. We will detail later why we take the market-specific factor approach. However, even though the fund flow to the stock market is relatively small, both the trust stock leverage factor LevFac-TS and aggregate leverage factor LevFac-TA explain the cross-sectional stock returns comparably better, with larger GMM t-statistics and R^2 values. These results are because the stock market involves more shadow banking activities through umbrella trusts and/or mezzanine trusts, which effectively encourage investors to lever up heavily in the stock market. In the responses to the negative 2015 policy shock, these leveraged investors sold stocks at fire-sale prices. The losses of these investors require compensation in the form of the significant prices of risk regressed against the leverage factors. We will further elaborate on this point in the return-based prices of risk in Section 4.2.

[Table 2 about here.]

We report the prices of risk regressed against the security leverage factor in Table 3. As we can see, the prices of risk regressed against the security leverage factor are insignificant in stocks and all assets in the benchmark models (3) and (10). Although the prices of risk against the security leverage factor in model (6) in bonds are significant, the GMM t-statistic is 2.17, which is slightly larger than the critical value of 2.07, resulting in significance at the 5% level. Therefore, we can conclude that the security leverage factor does not explain cross-sectional asset returns well across asset classes. These results are somewhat surprising because it is believed that securities companies are the key drivers behind the stock rally.

Similar results hold in a subsample of the pooled stocks that investors borrow from securities companies to trade: the trust stock and aggregate leverage factors outperform the security leverage factor[8]. For this purpose, we form these stocks into 15 portfolios and run the cross-sectional regression. The prices of risk regressed against the security leverage factor LevFac-S in the single- and two-factor models (1) and (2) are significant in Table 4; they are weakly significant just at the 10% level in the benchmark model (3) with the the GMM t-statistic 1.72 which is barley greater than the critical value 1.71 in Table 4. When compared with the trust leverage factors in the benchmark models, we immediately recognize the importance of the trust leverage factor relative to the security leverage factor. First, the GMM t-statistics for the trust leverage factor in models (6) and (9) are 2.63 and 1.91, respectively, both of which are higher than 1.72. Second, once we include both the security leverage factor and the trust leverage factor in the same models (10) and (11), the prices of risk regressed against the trust leverage factors and their significance are unchanged, whereas the prices of risks regressed against the security leverage factor become insignificant.

[Table 3 about here.]

[Table 4 about here.]

We elaborate on the differences between the trust leverage factor and security leverage factor here. The market prices the leverage risk of securities companies but not in a broad asset class. In one securities companies finance leveraged trades in the pooled stocks an hence the innovations in the security leverage measure the funding liquidity in trading the pooled stocks and not beyond. In the other securities companies financing is up to a limited amount under the rigorous regulation. Therefore, the security leverage possesses the power to explain asset returns in this subsample but not in a broad set of asset classes in that the innovations to the security leverage have very limited temporal variations. Empirical tests confirm this point. Differences in the prices of risk between the trust leverage and the security leverage

[8]We exclude the trust bond leverage factor because it is suitable for bonds only.

indicate that trust companies expose the market to the excessive leverage risks and that their leverage factors produce a great time variations to explain returns. Our results can by no means justify the CSRC's radical cracking down on the leverage-taking from "shadow" banks. However, we can indicate that the leveraged bets could be overwhelmingly reckless in borrowing the unregulated funds from "shadow" banks and that the risks are recognized by the market in China.

4.2 The Leverage Factor Mimicking Portfolio

Our leverage factors are not tradable. The factor prices of risk reported in Table2 are statistically significant but are not return-based. In order to understand the economic magnitude of these factors in the return basis, we construct leverage mimicking portfolios (LMP) and use their return as the risk factor analogous to that in AEM

$$LevFac_t = LMP_t + u_t,$$

where LMP represents the tradable leverage risk factor through a projection with the property $\mathrm{Cov}(LMP_t, u_t) = 0$. The cross-sectional regressions in the LMP approach are invariant in R^2, and the LMP factor prices of risk are deflated by $\frac{\mathrm{Var}(LevFac_t)}{\mathrm{Var}(LMP_t)}$. We regress the trust leverage factors against the excess returns of the tradable assets

$$\begin{aligned} LevFac\text{-}TS &= \gamma_s + \gamma_s'[HML, SBM, Mom]_t + u_{s,t} & (4.1) \\ LevFac\text{-}TB &= \gamma_b + \gamma_b'[DEF, TERM]_t + u_{b,t} & (4.2) \\ LevFac\text{-}TA &= \gamma_a + \gamma_a'[HML, SBM, Market, Mom, DEF, TERM]_t + u_{a,t}. & (4.3) \end{aligned}$$

To account for the differences between the stock market and the bond market, we use the different sets of excess asset returns as in Fama and French (1993) to deal with the two markets. We obtain three LMP return-based factors as follows:

$$\widehat{LMP\text{-}TS} = \hat{\gamma}_s'[HML, SBM, Market, Mom]_t \tag{4.4}$$

$$\widehat{LMP\text{-}TB} = \hat{\gamma}_b'[DEF, TERM]_t \tag{4.5}$$

$$\widehat{LMP\text{-}TA} = \hat{\gamma}_a'[HML, SBM, Mom, DEF, TERM]_t. \tag{4.6}$$

We redo the cross-sectional regression for the LMP factors in each asset class and report the LMP factor prices of risk in Table 5. We find that the prices of risk per quarter are still statistically significant in all asset classes in the benchmark models (3), (6), (9), (12) and (16). Specifically, the prices of risk are 7% against the trust stock leverage return-based factor LMP-TS in stocks; 3% against the trust bond leverage return-based factor LMP-TB in bonds; and 3%, 2% and 2% against the trust aggregate leverage return-based factor LMP-TA in equities, bonds, and all, respectively. The quarterly prices of risk multiplied by four give the annual counterparts, and these values are substantial. In the other models, the prices of risk are also evidently sizable. Note that the statistical significance values do not change. We observe an interesting pattern: the LMP-TS factor prices of risk in stocks are two times as high as the LMP-TB prices in bonds in the benchmark model, and the LMP-TA prices of risk in stocks are 1% higher than those in bonds and in all assets. This pattern also holds in other models and indicates that the stock market compensates more in bearing leverage risks than the bond market. This finding conforms to the fact that prosperous shadow banking activities and leveraged bets are concentrated in the stock market and that the leverage risks are priced in the bubble and bust of the stock market.

[Table 5 about here.]

We further run time series regressions to analyze the fitting performance of the LMP factors that rely on the Gibbons-Ross-Shanken (Gibbons et al. (1989)) F-statistic (GRS), which tests whether the alphas are jointly zero. In order to deal with the short time series, we first cut down the number of assets in each asset class to eliminate measurement errors. For stocks, we obtain 1 momentum portfolio and 6 stock portfolios by 2 size portfolios and 3 book-to-market-ratio portfolios. For bonds, we obtain 6 bond portfolios by 3 credit spread portfolios and 2 maturity portfolios. Secondly, we obtain the monthly series for LMP-TS, LMP-TB, and LMP-TA according to (4.4), (4.5) and (4.6), respectively, by multiplying the monthly portfolio returns with the γ estimated from the quarterly series. We regress the monthly portfolio returns against the monthly LMP factor to produce alphas that are the pricing error for the GRS test. We report the results in Table 6. We find that all LMP-TS, LMP-TB and LMP-TA factors are rejected in their corresponding asset classes. Consistent with AEM, the single LMP factor cannot outweigh the model with the factors used for its projection. For instance, the GRS F-statistic for LMP-TS in stocks is 3.57, 3.76 for the Fama-French 3 factor and 3.08 for Fama-French 3 factors plus momentum. This result implies that LMP-TS outperforms the Fama-French 3 factors and performs almost as well as the Fama-French 3 factors plus momentum. Be aware that the LMP-TS is the projection of the LevFac-TS onto four factors: HML, SMB, Market and Momentum. The results are comparable for LMP-TB and TMP-TA in bonds and all assets, respectively.

[Table 6 about here.]

4.3 Leverage Risk and Leverage Amplification

Our leverage-based CAPM representation has a critical parameter n that characterizes the leverage amplification. Since fund-matching companies are barely monitored by the regulatory body, there is no reliable source for this number unless it can be derived from the account-based trade data. We try to utilize the estimated prices of risk λ regressed against the leverage risk factor and the risk exposure to leverage risk to estimate this number. Our idea is to approximate the leverage-based CAPM using the two-factor model. Basically, we ask how tight the VaR constraint would need to be to produce the same effect of leverage risk on expectation. We solve for n by identifying the distortion term with the product of the leverage risk factor exposure and the factor price of risk.

$$y\frac{n\omega\sigma}{\bar{\sigma}}\phi = \beta_{LevFac}\lambda_{LevFac} \tag{4.7}$$

We calibrate the parameters to an representative investor who invests in the market portfolio for the sample considered in this article. The expected annual return and standard deviation of the market portfolio are R_m and σ, respectively. Denote this investor's wealth and leverage by P and L. Note that we take L as the ratio of the borrowed funds to the net wealth. The WMP is not guaranteed, and its expected annual return is $\tilde{R}_w$. The one-year risk-free deposit is R_f. We first pin down the shadow cost of constraint ϕ according to Garleanu and Pedersen (2011)

$$\phi = \tilde{R}_w - R_f.$$

We then determine $\bar{\sigma}$, representing the investor's maximum loss, by assuming three maximal loss rates, 10%, 20% and 30%, for a confidence level at 99% under the standard risk management in distress test. Then, $\bar{\sigma}$ is determined by the normal VaR calculation

$$\text{Loss rate} \times P = P \times (1 + L) \times \bar{\sigma} \times N(0.99).$$

We decide the relative consumption share y in a one-period model. To simplify the analysis, we assume that households allocate all their endowment to WMPs denoted by H at time zero[9]. Investors lever up to L to invest in the market portfolio. Then, the net wealth of the investor is H/L. At the end of the period, households can consume

[9]Considering deposits from households will result in a different number of parameter n but will not bring about new insights.

$$C_h = H \times (1 + \tilde{R}_w)$$

and the investor can consume

$$C_i = H/(1+L) \times (1 + R_m) + H \times (R_m - \tilde{R}_w).$$

The investor's relative consumption share is

$$y = C_i/(C_i + C_h).$$

The profit division rule ω is decided by (2.10) with the expectation

$$\omega = (\tilde{R}_w - R_f)/(R_m - R_f).$$

The calibration gives the parameters y, ω, σ, $\bar{\sigma}$, ϕ and $\beta_{LevFac}\lambda_{LevFac}$, which are necessary for determining n in (4.7) in stocks, bonds and all. Table 7 lists the values of these parameters and gives parameter n, by which the risk distortion that investor with leverage L requires is the same as the averaged leverage risk compensation offered in the market. A larger n represents more shadow banking activities. First, n is increasing in all assets, bonds, and stocks for the given distress test. This pattern implies that there is more leverage risk in the stock market as the result of shadow banking activities. Moreover, n is increasing in the maximal loss rate, which is equivalent to the maximal risk tolerance $\bar{\sigma}$ for the given asset class. This finding implies that a higher n accompanies more losses. The pattern of n once again supports the claim in Sections 4.1 and 4.2 that leverage amplification is concentrated in the stock market.

[Table 7 about here.]

4.4 Prediction Analysis

In this subsection, we discuss the return predictability of our factors. We regress the quarterly asset returns of an equally weighted portfolio within each class k against the lagged trust leverage risk factor

$$R^e_{k,t+1} = a_k + b_k LevFac_t + u_{t+1} \tag{4.8}$$

where LevFac$\in$ {LevFac-TS, LevFac-TB, LevFac-TA}.

[Table 8 about here.]

In Table 8 all coefficients b_k are negative in stocks, bonds, and all assets in all models, and the results are significant at the 1% level except for those of model (5), for which the significance is at the 5% level. The negative sign of the predictive coefficients follows the leveraged constraint intermediary asset pricing theory in the spirit of Adrian and Shin (2014) and Brunnermeier and Pedersen (2009). The high leverage is about become binding in the bad states and gives rise to positive innovation to leverage. The binding leverage constraint forces investors to deleverage in these bad states to satisfy capital requirements due to tightened funding liquidity. The deleveraging triggers asset fire-sales, which in turn decrease the expected future asset returns. Thus, the coefficient must be negative to imply a lower next-period return since the current-period leverage factor is positive. Leverage was extremely high in early 2015 before the CSRC suppressed taking excessive leverage from the shadow banks, and the innovations in leverage were positive at this time. The negative sign reflects the greatly decreased asset prices and hence low asset returns after the adverse policy shock.

4.5 Market-specific Factors

Section 4.1 and 4.2 discuss the prices of risk regressed against the market-specific factors LevFac-TS, LevFac-TB and LevFac-TA. A universal leverage factor explaining asset returns in each class would be ideal. Unfortunately, neither the trust stock leverage factor LevFac-TS in bond returns nor the trust bond leverage factor LevFac-TB in stock returns performs well. This section explains why we employ the market-specific leverage factor regression by looking at the market segementation.

[Table 9 about here.]

The trust stock leverage factor LevFac-TS performs poorly in bonds and all assets, as shown in Panel A in Table 9. None of the LevFac-TS factor prices of risk are significant in bonds or all assets except for in the single-factor model (4) in bonds. Specifically, the GMM t-statistics are less than 1.5 in the benchmark model for bonds and all assets. The same feature is found for the trust bond leverage factor LevFac-TB in Panel B, Table 9: LevFac-TS performs poorly in stocks and all assets. However, as witnessed already, the prices of risk regressed against the trust stock leverage factor are significant in stocks; the prices of risk against the trust bond leverage factor are significant in bonds. Theoretically, we require the trust leverage to be procyclical to explain asset returns. In Figure 2, Panel (a) shows that the trust stock leverage is procyclical in the stock market, and Panel (b) shows that the trust bond leverage is procyclical in the bond market. At the same time, we can see that the two indices representing the two markets do not move together and sometimes go against one another. We also note that procyclicality is much stronger for the trust stock leverage in the stock market in the sample[10]. Therefore, we decide to use such market-specific leverage factors[11]. A single leverage factor is preferred to explain the returns across multiple asset classes, as in HKM. Having such a factor is of interest. Our paper does not pursue this direction, and we leave this matter for future research.

[Figure 2 about here.]

[10]This dynamic is the reason that the prices of risk against the trust stock leverage are higher than those against the trust bond leverage factor.

[11]The trust aggregate factor does a fairly good job; however, the power of this factor is weakened because the two other factors trade off one another.

5 Robustness Analysis

This section provides robustness checks for our leverage factors in terms of the factor race and the sample size.

5.1 Factor Race

We show the statistical and economic significance of the prices of risk regressed against the trust leverage risk factors in the cross-sectional regressions, including the factors Market, DEF and TERM. It is interesting to ask whether these factors can survive a factor race against other commonly studied risk factors in the asset pricing literature. In addition to the Market, DEF, TERM factors, Tables 10, 11, 12, and 13 show a factor race between each of three trust leverage factors and the Fama and French (1993) three-factor model, the Fama-French three-factor model plus Carhart (1997) a momentum factor, the Fama and French (2015) five-factor model plus a momentum factor, the Fama-French five-factor model plus momentum and the Pástor and Stambaugh (2003) liquidity factor. Each trust leverage factor still possesses significant explanatory power in the cross-sectional regressions as before in the factor race. Specifically, the prices of risk regressed against the trust stock leverage factor LevFac-TS are from 0.22-0.23 at the 1% significance level in stocks in four comparison cases. The prices of risk regressed against the trust bond leverage factor LevFac-TB are 0.11 and 0.13 at a 1% significance level in bonds when compared with the Fama-French three factors and the Fama-French three factors plus momentum. The prices of risk decrease to 0.7 and 0.8 at a reduced significance level 10% in both the Fama-French five factors and the Fama-French five factors plus momentum factor. The prices of risk regressed against the trust aggregate leverage factor LevFac-TA range between 0.06 and 0.12 in stocks, bonds and all assets and are significant at the level 10%. We conclude that the trust leverage factors are robust against the commonly used risk factors. Moreover, the prices of risk regressed against both the trust stock leverage factor and trust aggregate leverage factor in stocks are larger than those against the other trust leverage factors in bonds and all assets in the factor race. The finding again confirms our assertion that the leveraged risks from shadow banking activities are concentrated in the stock market and are priced by the market.

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

5.2 Monthly Frequency Analysis

The short times series cast doubt on the robustness of our results. To justify, one approach is to obtain monthly LMP factors, as in the GRS test in Section 4.2, and run cross-sectional regressions on the monthly LMP factors, for which we have a factor series of 78 months. Our results hold for the monthly LMP factors. An indirect approach is to study the monthly trust aggregate leverage factor as defined in Section 3.1 and derived from the online trust data. We also apply the projection technique to produce the return-based monthly trust aggregate LMP factor. We run the cross-sectional asset pricing tests on both the monthly trust aggregate leverage factor and the monthly trust aggregate LMP factor. The results are presented in Table 14 and Table 15. Both the monthly trust aggregate leverage factor LevFac-TA(m) and the monthly trust aggregate return-based leverage factor LMP-TA(m) produce significant prices of risk in the three asset classes, as shown in Table 14 and Table 15. For instance, the prices of risk regressed against the monthly trust aggregate leverage factor LevFac-TA(m) are significant at the 1% level in the benchmark models (3), (6) and (11) across stocks, bonds and all assets. Moreover, the prices of risk are in stocks are the largest among three asset classes, which again confirms that leveraged investments in the stock market are driven by shadow bank lending. We note that the monthly factor yields smaller prices of risk and lower R^2 values because the construction of the monthly leverage factor cannot fully capture the variation of the true trust leverage factor as the trust companies don't post all the trust plans.

[Table 14 about here.]

[Table 15 about here.]

6 Concluding Remarks

We document the leverage magnification in shadow banking activities and build a leverage-based asset pricing model to reflect leverage risks and asset prices. Based on this model, we conjecture that intermediary leverage measures the state price of density and that leverage risks rising from the shadow banks should be priced in China. Using the trust leverage for the pricing factor, we discover that the cross-sectional prices of risk regressed against the trust leverage factors are statistically and economically significant and that the trust leverage factors possess predictive power for the future expected return. Our results show that the intermediary asset pricing theory holds not only for the mature financial market in the U.S. but also in the immature emerging market in China. Specifically, leverage risks originated from the leverage amplifications stemming from bank-trust cooperation. The empirical tests show that leverage risks are concentrated in the stock market with more significant and higher prices of risk for the leverage risk in stocks. These findings are useful for understanding the regulatory concern and crackdown on unregulated shadow banking lending.

There are several things that we can do better to understand the asset prices and the leverage risks in emerging market. One is if we can identify the better leverage risk factor as done in AEM to price each asset class. This requires researchers to investigate the intermediaries representing the shadow banks and exploit the data regarding leverage. The other is if we study more off-balance instruments other than WMPs. Our paper build a connection between the unregulated WMPs and the trust AUM. We have not studied the entrusted loan that is also important in the shadow banking activities. We leave them for the future research.

Appendix

A Shadow Banking Lending and Leveraged Investments

It is arguably agreed that the flood of credit created in shadow banking increased investment leverage and stimulated stock prices by up to 150 percent from June 2014 to June 2015 in China. Chen, He, and Liu (2017) show that China's four-trillion-yuan stimulus package in 2009 resulted in a credit flood in shadow banking from 2012. This unregulated leverage arrived at such an unprecedented level that the Chinese Securities Regulatory Commission (henceforth, CSRC) took radical actions to crack down on leveraged investments in April 2015[12]. Under the toughest government intervention on lending, coupled with the panics, investors were forced to delever and fire-sell assets, which plummeted asset prices. One third of the value of A-shares on the Shanghai Stock Exchange was wiped off within one month of the event.

This section is devoted to show how investors increase their investment leverage through

[12]The CSRC announced a new limit on margin lending for stock brokerages June 12, 2015 while also reiterating the ban on illicit margin trading through mechanisms such as umbrella trusts. For the latter, refer to the CSRC regulatory document cracking down on unregulated borrowing "Notice on Regulating Illegal Activities in Securities Trading" (document no. 19, 12 July, 2015). See `http://www.csrc.gov.cn/pub/zjhpublic/G00306201/201507/P020150712642807188999.pdf`.

either having the brokerage borrow from a securities company or through"shadow" borrowing from a trust company. A securities company must book brokerage loans on the balance sheet as the downside risk of lending is limited. In contrast, a trust company receives and lends off-balance sheet WMPs funds under much less regulation. This section helps us understand how the unregulated funds from shadow banks can lift leverage much higher than expected and how such funds service the formulation of our leveraged-based asset pricing model.

A.1 Margin Trading and Short-selling

China's leveraged security investment via brokerage lending officially took off on February 12, 2010. Securities companies are the only legitimate financial institutions eligible for brokerage lending. These companies are independent brokers that are not owned by other institutions. The CSRC launched the margin trading and short-selling pilot program in 2010. Under the initial pilot program, investors can margin trade and short-sell 90 selected stocks. The CSRC expanded the program several times, and the program contained 904 stocks as of September 2016. Figure 3 shows that the amount of officially sanctioned margin trading in the Chinese stock market ballooned and hit a peak of 9% of GDP in the second quarter of 2015. The broad media coverage seemingly implies a belief that brokerage lending greatly contributed to the stock market rally but without substantiation. Additionally, a critical feature of brokerage lending is that major securities companies enforce a typical minimum margin requirement of 50% for investors, converting to a maximum investment leverage (assets/equity) ratio of 2. This greatly restricts the brokerage leverage risks and variations therein.

[Figure 3 about here.]

A.2 WPMs and Bank-Trust Cooperation

How do leverage risks arise and how are these risks linked to the asset market? This section addresses these issues. We discuss what WMPs are and how WMP funds flow into the asset market and amplify investment leverage through a cooperation between banks and trust companies (bank-trust cooperation). Acharya et al. (2016) show that a tremendous amount of WMPs, raised by banks and financial institutions from households, are unguaranteed funds that circumvent the three Chinese banking regulatory requirements[13] and exploiting regulatory arbitrages. WMPs are effectively structural instruments that are underlined by long-term risky assets, featuring short maturity periods and high yields. Figure 4a shows that the non-guaranteed WMPs not only dominate but also outpace guaranteed WMPs. Figure 5a and Figure 5b show that WMPs offer an average return in excess of 1%-3% over one year and that approximately 60% of WMPs have maturities of less than three months. Diamond and Dybvig (1983) maturity mismatch realizes the high yield of WMPs, the redemption of which relies on how the underlying risky assets perform.

Let us look at how the WMPs are associated with the trust AUM. Banks generally use a "channel" firm to raise the WMP funds so that WMPs are off the bank balance sheet and exempted from the regulatory requirements. Trust companies act as such channel firms and often are the most important. Interestingly, Figure 4b indicates that the size and growth of the WMPs are noticeably consistent with those of the trust AUM before 2015 and are clearly differentiated since the CRCS cut off cooperation between banks and trusts. Hachem and Song (2016) document the same pattern and show that WMPs funds are the main sources of the AUM of trusts. More importantly, trust companies can lend to any sector without

[13]The first is the capital requirement, similar to the international Basel Accords. The CBRC currently requires a minimum capital adequacy of 8%, will ask 11.5% for systemically important banks and will require 10.5% for all other banks by the end of 2018. The second requirement is a ceiling on bank deposit rates set by the People's Bank of China (China's central bank, PBoC). The third requirement is a 75% cap on bank loan-to-deposit ratios, meaning that each commercial bank can only lend up to 75% of its deposits.

subject to bank limits on loan or deposit rates ceiling, and at the same time avoid costly PBoC reserve requirements. This is the reason that we define the trust companies as the main bodies of shadow banks.

[Figure 4 about here.]

[Figure 5 about here.]

After the WMPs are identified as the main sources of funding to trust companies, we explain how the WMP funds flow to the asset market and amplify leverage. This explanation requires us to recognize two things: First, WMPs are essentially structural instruments that are sliced into different tranches and then sold to investors. The junior tranche investors take the first losses from the underlying risky asset but enjoy all of the profits lefts over. The senior tranche investors receive a fixed return with credit protection from losses starting in the junior tranche. Second, the junior tranche of the WMP is pegged to a trust plan such that the WMP funds are transferred to the trust company AUM invested in the risky assets, including financial assets. The WMP return and its redemption are contingent on the risky assets. In other words, the junior tranche investors effectively borrow from the senior tranche investors in the WMP and invest in the risky assets indirectly through the trust company. Putting everything together with the banks that get involved with the unguaranteed WMPs invested in the risky asset, we characterize this mechanism in Figure 6a and refer to this as a shadow banking activity in a bank-trust cooperation relationship whenever shadow banking activities are discussed in this paper.

Finally, we come to see how such shadow banking activity results in enormous leverage in the asset market. We investigate a chain of WMP fund transfers involving households, bank-trusts, securities companies, a universe of so-called "fund matching" firms often registered as consulting companies, and the asset market.

[Figure 6 about here.]

Two popular trust plans, including umbrella trusts and mezzanine trusts, receive the WMP funds and invest them in the risky asset. We carefully detail umbrella trusts and explain mezzanine trusts in the Appendix. An umbrella trust works as follows. We study cases with and without a fund-matching company. Figure 6 explains this mechanism without a fund-matching company. A trust company subscribes to the senior tranche of a WMP, and investors, such as hedge funds and institutions, subscribe to the junior tranche[14]. In the figure, the junior tranche investors are effectively borrowing three extra dollars against their wealth of one dollar to bet indirectly on the risky asset in the form of the trust plan. In practice, the junior tranche is often pegged to a trust plan with the help of a securities company. For purposes of exposition, we call a trust plan a trust account. We assume that the junior tranche investors divide a trust account into three sub-accounts, with each sub-account ideally holding one and one-third dollar. There are three other investors 1, 2, and 3, coming to trade on the three sub-accounts, respectively, by reserving one third of a dollar or the value-equivalent asset. For simplicity, we neglect the fees charged. Investor 1, 2, or 3 effectively borrows the senior tranche of one dollar against his one-third of a dollar to invest in the risky asset market. The junior tranche investors are the official trust account holders and maintain the ultimate control over these sub-accounts. These investors can liquidate any sub-account if any of the three investors racks up heavy losses on his sub-account. Of course, the junior tranche investors do not necessarily divide but rather invest directly in the risky asset market on their own. The leverage of each junior tranche investor is 3 in this case.

If a fund-matching company gets involved in the WMP fund transfer, leverage can grow wildly. In Figure 7, a fund-matching company rather than a trust company subscribes to

[14]Banks can also subscribe to the senior tranche of a WMP. As trust companies represent shadow banks in China, we focus on such entities here.

the junior tranche of WMP 1, which is pegged to trust account 1. When the fund-matching company divides trust account 1 into sub-accounts and requires a reserve from investors 1, 2, and 3, in contrast with Figure 6, the company chooses to accept only the upfront cash from investors 1, 2, and 3. For illustrative purposes, we assume that each investor has to deposit one third of a dollar in cash up front. Thus, the fund-matching company collects a dollar of cash, which allows it to subscribe to the junior tranche of WMP 2, which is pegged to trust account 2. The company divides trust account 2 and grants sub-accounts to investors 4, 5, and 6 by asking again for upfront cash totaling to one dollar. The fund-matching company 's leverage rises to 6 while that of each investor remains at 3. Suppose that the fund-matching company can continue doing this process by going to WMP 3. Obviously, the leverage of the company becomes 9, and that of each investor becomes 3. The fund-matching firm controls the risk exposures of all the trust accounts. A striking feature of such a mechanism is that no one, including the regulatory body, knows exactly how many times a fund-matching company can repeatedly do this. The CSRC fretted over leverage risks caused by umbrella trusts and stepped up in April 2015 to clear up umbrella trusts by cutting off their connections to securities companies. We call this radical action a negative policy shock to leverage.

[Figure 7 about here.]

B Mezzanine Trusts

Figure 8 shows a mezzanine trust with a fund-matching company. As before, a mezzanine trust pegged to a WMP consists of a senior tranche, mezzanine tranche, and junior tranche with ratios $3{:}\frac{1}{2}{:}\frac{1}{2}$ or 6:1:1, as in the figure. The trust company subscribes to the senior tranche with six dollars; the fund-matching company subscribes to the mezzanine tranche with one dollar; investors subscribe to the junior tranche with one dollar. The fund-matching company receives a fixed return but is superior to the trust company. The fund-matching company is classified as if it were a junior tranche investor. In this way, investors in the trust account lever up to 3 but effectively up to 6 dollars. Again, the fund-matching company has the right to liquidate the trust account whenever its risk threshold is triggered.

[Figure 8 about here.]

A mezzanine trust has the same asset pricing implication. We assume that the ratio between senior, mezzanine and junior tranches is $n\alpha_t : n-1 : 1$. Thus, investors lever up to $n\alpha_t$ even though it looks like $n\alpha_t : (n-1+1) = \alpha_t$. We assume that fund-matching companies grab a fraction ω_t of the profits earned from risky assets on behalf of the senior tranche holders. We do not need to model how fund-matching companies and senior tranche holders split the profit fraction ω. Analogous to (2.12 and 2.13), fund-matching companies maximize

$$\max_{\alpha_t}[\omega_t(n\alpha_t + n - 1)(\mu_t - r_t) + r_t] \tag{B.1}$$

subject to

$$\omega_t^2(n\alpha_t + n - 1)^2\sigma_t^2 \leq \bar{\sigma}^2. \tag{B.2}$$

The optimization problem for investors is the same as before:

$$\max_{\alpha_{i,t}}[(\omega_t + (1-\omega_t)\alpha_{i,t})(\mu_t - r_t) + r_t] - \frac{1}{2}(\omega_t + (1-\omega_t)\alpha_{i,t})^2\sigma_t^2 \tag{B.3}$$

subject to a slightly changed constraint

$$\alpha_{i,t} \leq n\alpha_t. \tag{B.4}$$

With positive net expected profits of $\mu_t - r > 0$, fund-matching companies take the highest leverage

$$\frac{\bar{\sigma}}{n\omega_t\sigma_t} - \frac{(n-1)}{n}.$$

Investors' leverage, if their leverage constraint is binding, becomes

$$\alpha_{i,t} = \frac{\bar{\sigma}}{\omega_t\sigma_t} - (n-1). \tag{B.5}$$

This approach for the umbrella trust follows the same analysis, and the leveraged-CAMP holds under a positive net expected profit.

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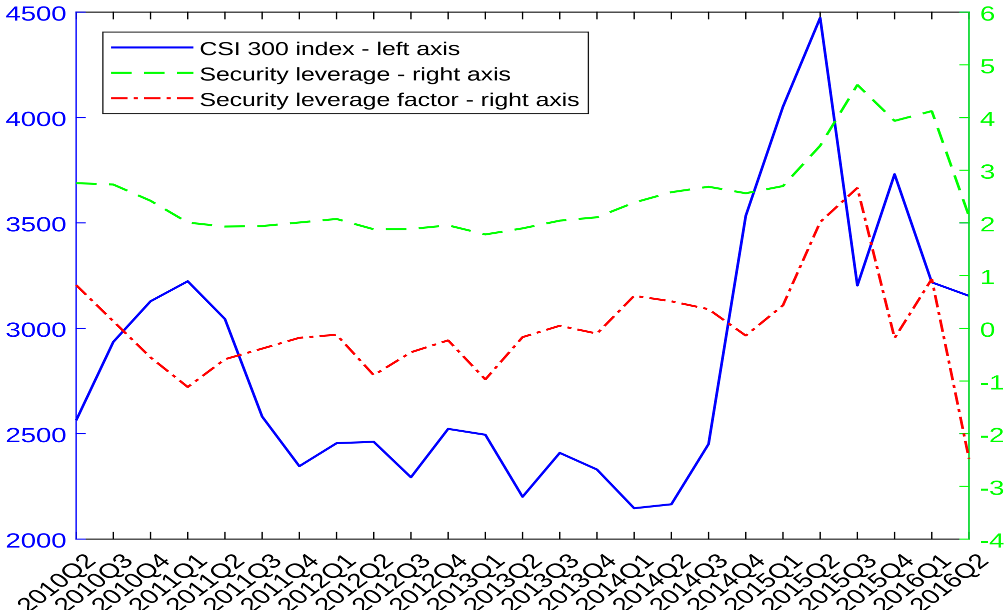
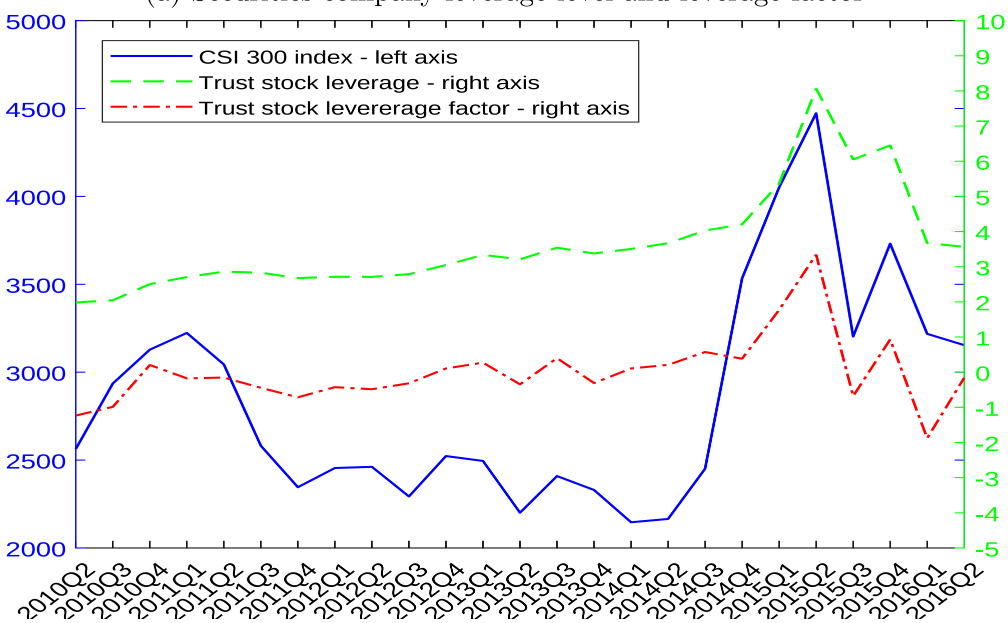
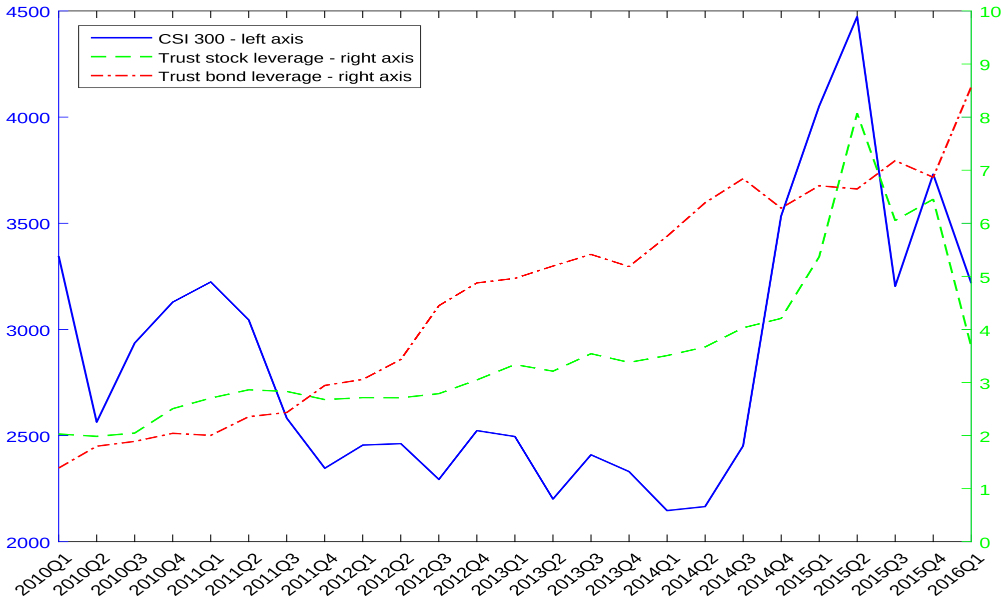


(a) Securities company leverage level and leverage factor

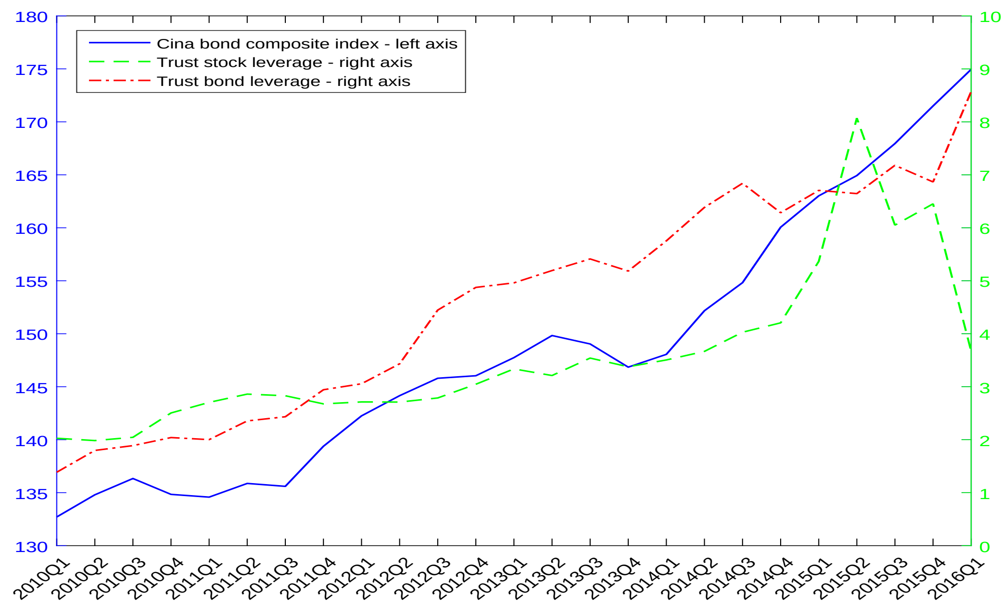


(b) Trust leverage level and leverage factor

Figure 1: The figure shows leverage and leverage factor of securities company and trust. Both leverage and leverage factor time-series are standardized to zero mean and unit variance for illustration. Data are quarterly, 2010Q2:2026Q2, from from Wind and China Trustee Association



(a) Trust bond leverage vs bond index



(b) Trust bond leverage vs bond index

Figure 2: The figure shows the trust stock leverage vs the stock index, and the bond leverage vs the bond index. Data are quarterly, 2010Q2:2026Q2, from from Wind and China Trustee Association

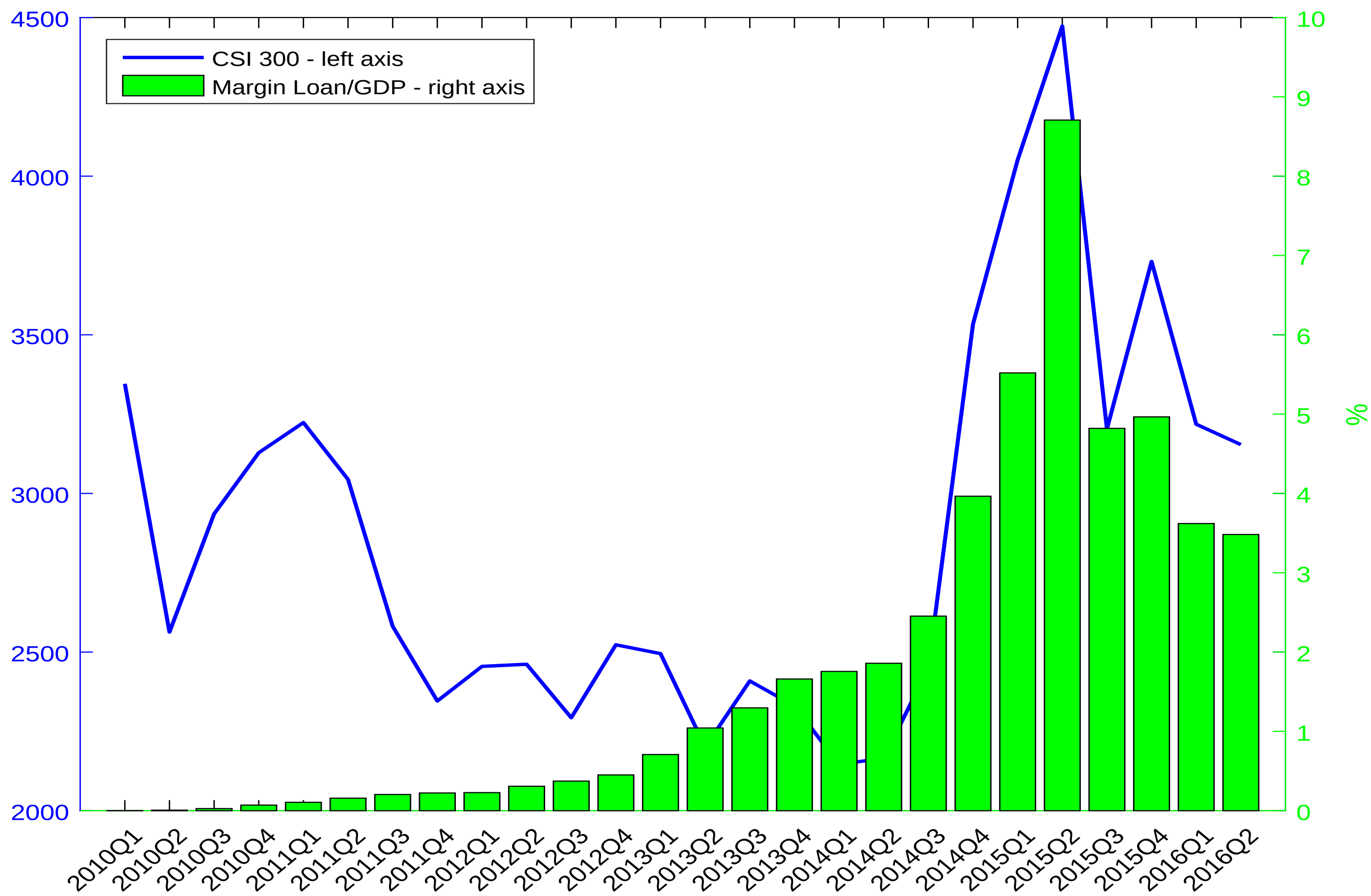
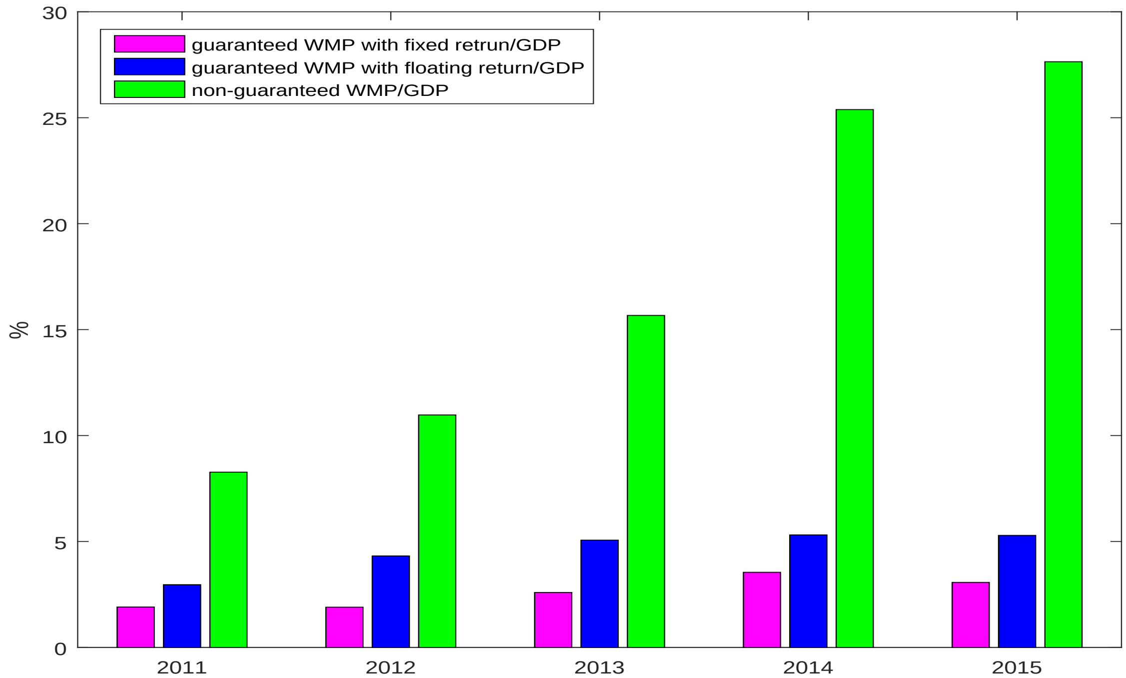
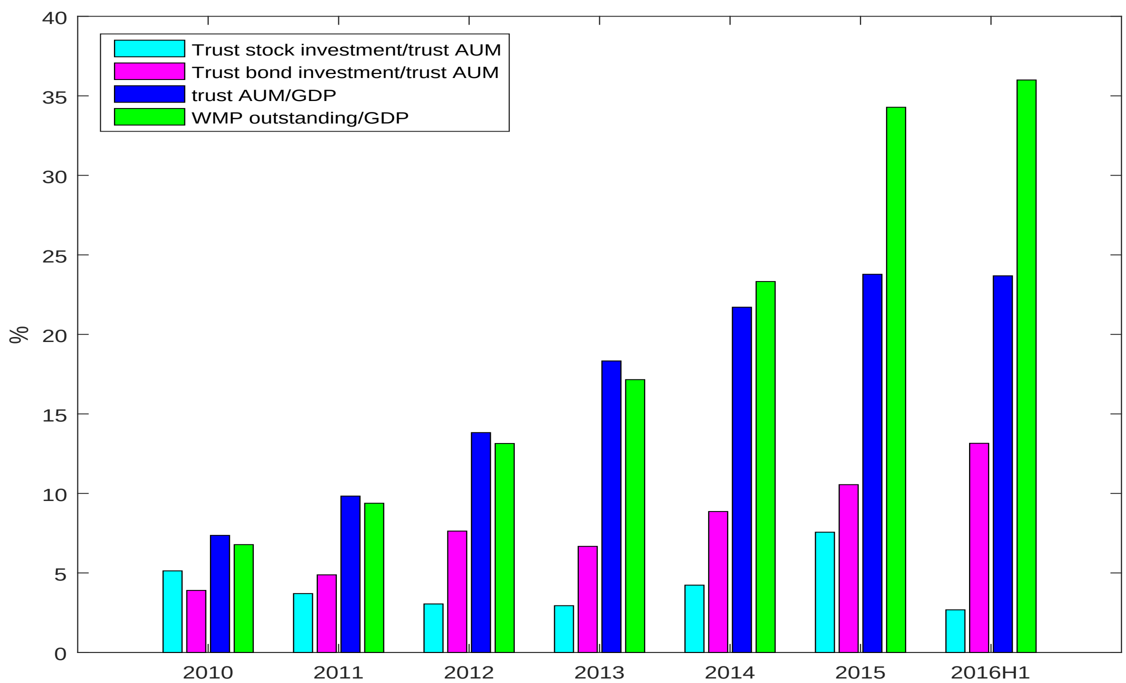


Figure 3: Margin Loan and CSI 300 Index
The figure shows the quarterly ratio of the aggregate margin loan to GDP and the Shanghai Stock Index. Data source: Wind.

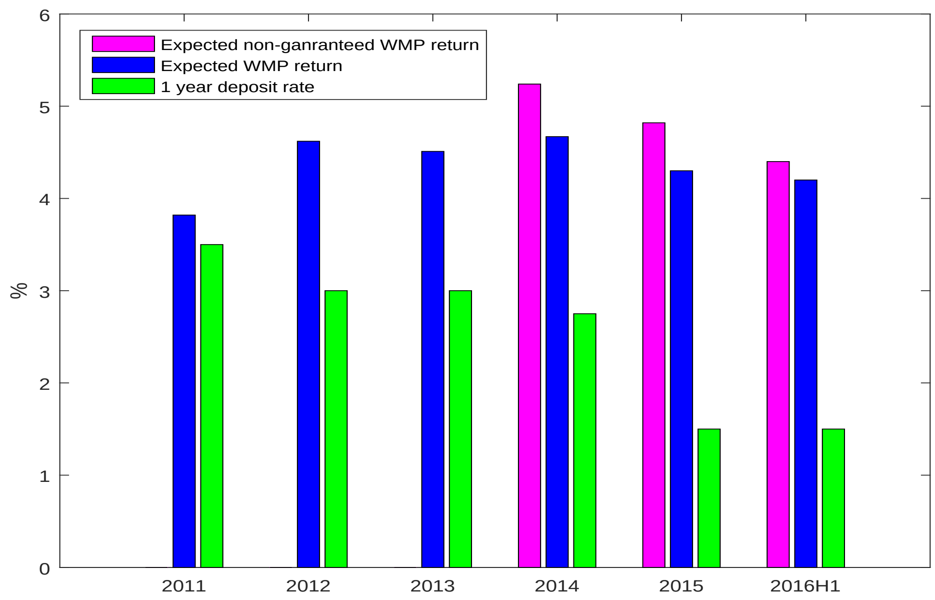


(a) Guaranteed and Non-guaranteed WMP

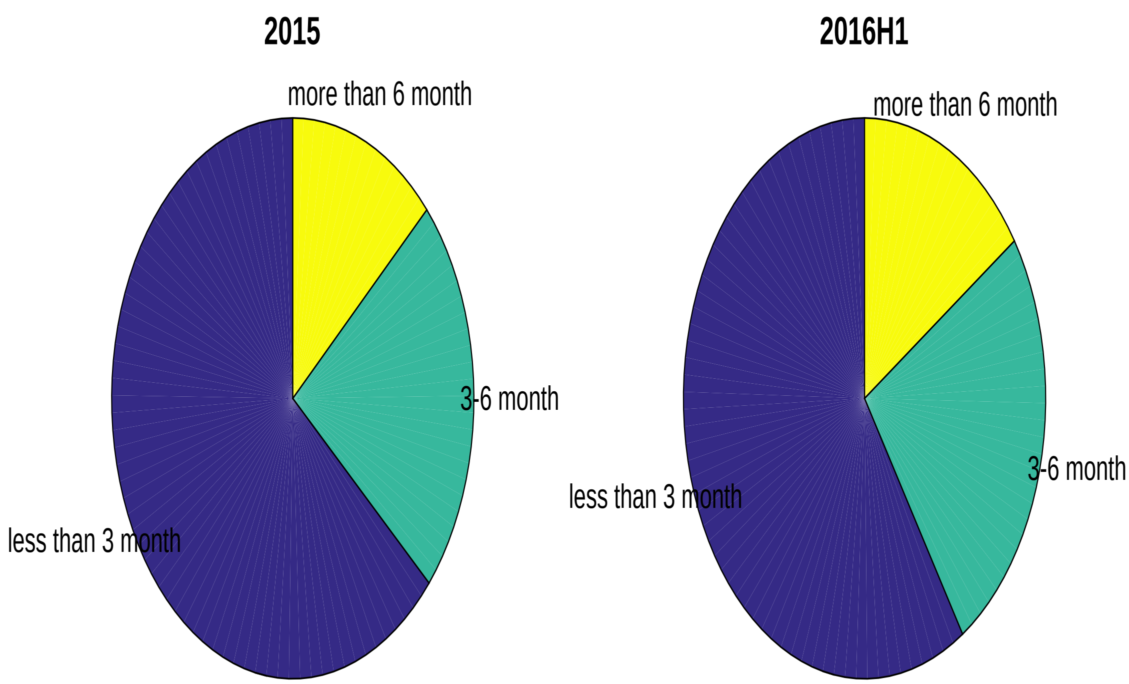


(b) WMP outstanding and trust AUM

Figure 4: Panel (a) shows the proportion of guaranteed and non-guaranteed WMPs relative to GDP. Panel (b) shows WMP outstanding, trust asset under management. Data: trust data from Wind and WMPs data from China Central Depository & Clearing Co.,Ltd

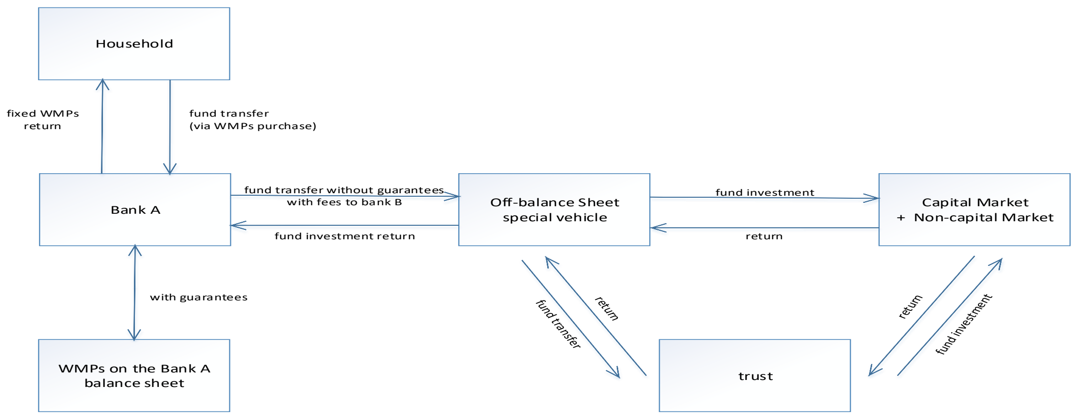


(a) WMP Annualized Return

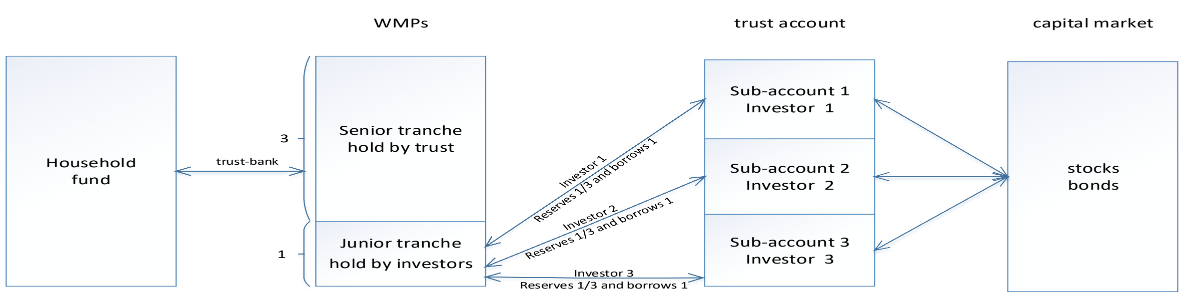


(b) WMP Maturity

Figure 5: Panel (a) shows WMP annual return against deposit rate. Panel (b) shows WMP maturity in 2015 and in the first half of 2016. Data: trust data from Wind and WMPs data from China Central Depository & Clearing Co.,Ltd



(a) Off-balance sheet WMP through trust-bank cooperation



(b) Umbrella trust without fund-matching firm

Figure 6: The figure illustrates the off-balance sheet WMP through trust-bank cooperation and investment leverage in an umbrella trust when there is no fund-matching company amplifying leverage

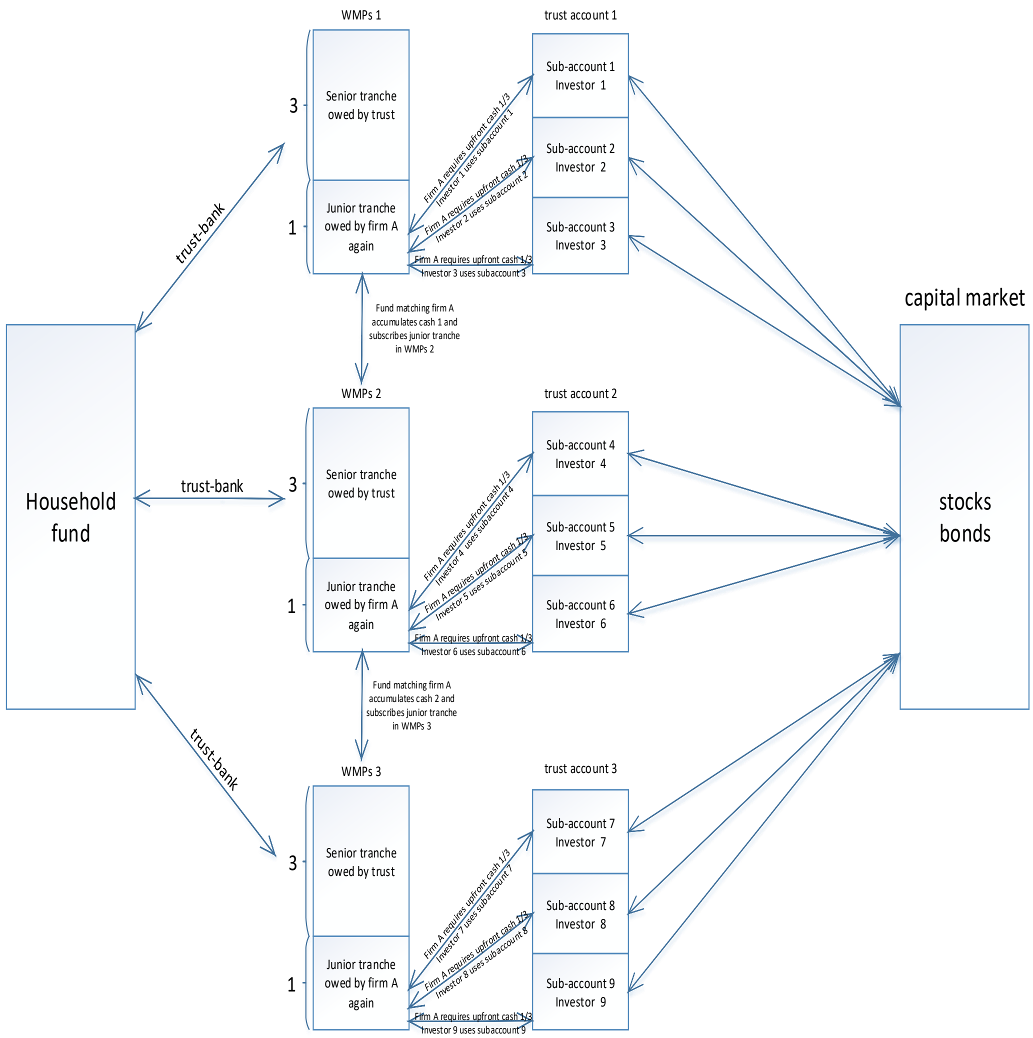


Figure 7: The chart flow demonstrate the leverage magnification in the credit transformation channelled by fund-matching firm in an umbrella trust

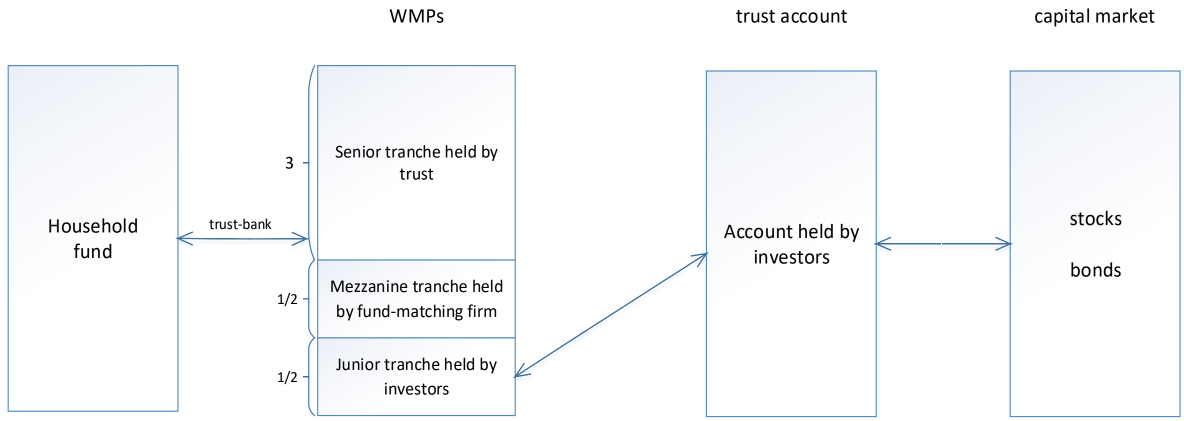


Figure 8: The chart flow demonstrate the leverage magnification in the credit transformation channelled by fund-matching firm in a mezzanine trust

Table 1: Leverage and Leverage Factor Describe Statistic
This table presents asset under management of both trust companies and security companies, correlation of leverage level and leverage factor. Data are quarterly 2010Q1:2016Q2.

Pane A: Asset under Managemet of Trust Companies and Listed Securities Companies					
	Mean	Std. Dev	Median	Max	Min
Trust Companies(In Billions CNY):					
Investment in Stock	372.87	329.38	256.04	1411.55	79.30
Investment in Fund	103.26	103.65	63.76	329.65	8.72
Investment in Bond	720.89	601.93	596.19	2015.52	39.32
Investment in Financial Market (Online Data)	584.92	470.07	437.44	1685.50	57.01
Total Equity	165.50	59.02	150.83	277.54	89.28
Listed Security Companies (In Billions CNY):					
Total Asset	1905.99	1802.61	1059.13	6763.73	316.25
Total Equity	678.53	448.56	518.80	1952.07	148.50
Trusts (Proportion of GDP %):					
Investment in Stock	2.41	1.78	1.79	8.42	0.80
Investment in Fund	0.64	0.58	0.42	1.73	0.10
Investment in Bond	4.55	3.38	4.18	12.45	0.45
Investment in Financial Market (Online Data)	3.71	2.55	3.10	8.68	0.65
Total Equity	1.13	0.23	1.06	1.66	0.87
Listed Security Companies (Proportion of GDP %):					
Total Asset	12.51	10.01	8.18	40.34	1.76
Total Equity	4.59	2.46	3.77	11.64	0.83

Pane B: Leverage Factor Correlation					
	Lev-TS	Lev-TB	Lev-TA	Lev-S	Lev-TA(q)
Lev-TS	1.00				
Lev-TB	0.68	1.00			
Lev-TA	0.88	0.95	1.00		
Lev-S	0.65	0.50	0.62	1.00	
Lev-TA(q)	0.87	0.94	0.99	0.65	1.00

Pane C: Leverage Factor Correlation					
	LevFac-TS	LevFac-TB	LevFac-TA	LevFac-S	LevFac-TA(q)
LevFac-TS	1.00				
LevFac-TB	-0.35	1.00			
LevFac-TA	0.77	0.31	1.00		
LevFac-S	0.02	0.27	0.14	1.00	
LevFac-TA(q)	0.65	0.25	0.85	0.18	1.00

Table 2: Trust Leverage Risk Factor Performance

This table presents the trust leverage prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spread, and 50 asset portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in the asset class specific to leverage factor. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock			Bond			Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LevFac-TS	0.16	0.23	0.21													
t-FM	2.59	4.99	4.55													
t-GMM	2.48	3.85	3.42													
LevFac-TB				0.12	0.09	0.14										
t-FM				2.81	2.37	3.49										
t-GMM				2.68	2.32	3.20										
LevFac-TA							0.18	0.22	0.13	0.06	0.08	0.11	0.06	0.07	0.09	0.10
t-FM							2.75	3.61	2.79	1.81	2.98	4.85	2.26	2.44	3.24	3.90
t-GMM							2.55	2.54	2.24	1.80	2.92	4.25	2.25	2.44	3.10	3.71
DEF			0.01		0.03	0.03			-0.00		0.03	0.04			0.03	0.03
t-FM			0.94		3.65	4.26			-0.36		3.94	5.07			4.33	4.31
t-GMM			0.94		3.26	3.94			-0.30		3.54	4.81			4.12	3.78
TERM			-0.25		0.05	0.04			-0.17		0.05	0.03			0.03	0.04
t-FM			-4.54		1.85	1.42			-3.99		1.86	1.13			1.21	1.41
t-GMM			-3.32		1.85	1.41			-3.39		1.86	1.11			1.20	1.39
Market		0.01	0.02			-0.16		0.11	0.06			-0.22		-0.02		-0.02
t-FM		0.11	0.42			-2.85		2.52	1.33			-3.75		-0.44		-0.57
t-GMM		0.10	0.42			-2.29		1.88	1.23			-2.73		-0.41		-0.52
Intercept	0.02	0.02	0.01	0.05	0.05	0.05	0.05	-0.09	-0.04	0.05	0.05	0.06	0.05	0.06	0.05	0.06
t-FM	0.62	0.87	0.21	7.47	6.84	6.84	1.28	-2.89	-1.12	7.42	6.87	6.99	2.81	7.64	2.81	7.24
t-GMM	0.62	0.87	0.21	7.47	6.84	6.84	1.28	-2.89	-1.12	7.42	6.87	6.99	2.81	7.64	2.81	7.24
Adj R^2	0.20	0.24	0.57	0.06	0.29	0.34	0.24	0.46	0.59	0.05	0.28	0.35	0.04	0.31	0.21	0.49
MAPE %	2.59	2.57	1.05	6.94	5.18	5.00	2.15	1.53	1.08	7.19	4.83	4.22	4.89	4.85	3.84	3.78
Assets	25	25	25	25	25	25	25	25	25	25	25	25	50	50	50	50
Quarters	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26

Table 3: Securities Firm Leverage Risk Factor Performance

This table presents the security leverage prices of risk for the 25 size and book-to-market stock portfolio, 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combining stock and bond. Each model is estimated as (3.2) with the security leverage factor LevFac-S in the asset class specific to leverage factor. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LevFac-S	-0.29	-0.47	-0.12	-0.01	0.12	0.13	-0.01	-0.03	0.06	0.04
t-FM	-2.08	-3.66	-1.58	-0.20	1.97	2.25	-0.19	-0.60	0.74	0.74
t-GMM	-1.92	-3.34	-1.58	-0.20	1.92	2.17	-0.19	-0.58	0.74	0.74
DEF			0.00		0.03	0.04			0.04	0.03
t-FM			0.27		3.79	4.39			4.23	4.21
t-GMM			0.12		3.53	4.17			3.97	3.80
TERM			-0.12		0.04	0.03			0.02	0.03
t-FM			-3.69		1.55	1.21			0.86	1.02
t-GMM			-3.67		1.55	1.19			0.84	1.00
Market		0.22	0.13			-0.12		-0.01		-0.01
t-FM		5.01	3.13			-2.01		-0.23		-0.37
t-GMM		2.41	2.09			-1.75		-0.22		-0.34
Intercept	0.00	-0.18	-0.10	0.06	0.05	0.05	0.05	0.06	0.05	0.05
t-FM	0.10	-6.41	-4.18	7.57	6.97	7.02	3.24	7.44	3.19	7.30
t-GMM	0.10	-6.41	-4.18	7.57	6.97	7.02	3.24	7.44	3.19	7.30
Adj R^2	0.26	0.48	0.67	0.09	0.37	0.44	0.11	0.34	0.30	0.52
MAPE %	2.40	1.78	0.97	7.28	5.29	5.14	5.07	4.95	4.15	4.12
Portfolio	25	25	25	25	25	25	50	50	50	50
Quarters	26	26	26	26	26	26	26	26	26	26

Table 4: Trust Leverage Risk Factor vs Securities Firm Leverage Risk Factor
This table compare pricing results between the security leverage factor and the trust leverage factor for the 15 size and book-to-market stock portfolios formed from stocks that investors borrow from security companies to trade. Each model is estimated as (3.2) with the security leverage factor LevFac-S, two trust leverage factors LevFac-TS and LevFac-TA. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

Margin Trading and Short Selling Portfolios											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LevFac-S	0.14	0.24	0.11							0.06	0.08
t-FM	3.30	3.63	1.84							0.92	1.22
t-GMM	3.03	2.89	1.72							0.88	1.20
LevFac-TS				0.23	0.24	0.26				0.27	
t-FM				3.03	3.15	3.28				3.42	
t-GMM				2.80	2.50	2.63				2.69	
LevFac-TA							0.09	0.11	0.17		0.17
t-FM							1.95	2.24	1.98		1.98
t-GMM							1.68	2.24	1.91		1.90
DEF			-0.02			-0.02			-0.01	-0.02	-0.01
t-FM			-1.29			-1.85			-1.02	-1.87	-0.91
t-GMM			-1.26			-1.82			-0.94	-1.80	-0.84
TERM			-0.16			-0.18			-0.16	-0.18	-0.15
t-FM			-4.36			-4.66			-4.40	-4.63	-4.37
t-GMM			-3.31			-3.72			-3.20	-3.76	-3.19
Market		0.06	0.03		0.15	0.06		0.04	0.02	0.07	0.02
t-FM		0.73	0.44		1.53	0.99		0.73	0.31	1.09	0.31
t-GMM		0.72	0.44		1.36	0.95		0.67	0.31	1.03	0.31
Intercept	0.10	-0.02	0.00	-0.10	-0.10	-0.03	-0.05	0.09	0.01	-0.04	0.01
t-FM	3.34	-0.27	-0.04	-1.11	-1.15	-0.61	-0.92	1.70	0.26	-0.74	0.26
t-GMM	3.34	-0.27	-0.04	-1.11	-1.15	-0.61	-0.92	1.70	0.26	-0.74	0.26
Adj R^2	0.13	0.31	0.62	0.19	0.34	0.64	0.34	0.52	0.65	0.66	0.68
MAPE %	2.37	2.22	1.32	2.50	2.09	1.26	2.15	1.55	1.29	1.22	1.27
Assets	15	15	15	15	15	15	15	15	15	15	15
Quarters	26	26	26	26	26	26	26	26	26	26	26

Table 5: LMP Factor Performance

This table presents the the trust leverage return-based prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage return-based factors LMP-TS, LMP-TB and LMP-TA in the asset class specific to leverage factor. Three return-based leverage factors LMP-TS, LMP-TB and LMP-TA are obtained according to (4.4), (4.5) and (4.6). Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock			Bond			Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LevFac-TS	0.05	0.08	0.07													
t-FM	1.92	4.07	3.54													
t-GMM	1.82	3.81	3.03													
LevFac-TB				0.04	0.02	0.03										
t-FM				3.89	2.57	3.51										
t-GMM				3.87	2.32	3.39										
LevFac-TA							0.04	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02
t-FM							2.27	3.62	2.82	2.65	3.12	5.04	3.11	3.11	4.70	4.16
t-GMM							2.27	1.50	1.89	1.89	2.87	3.39	2.65	2.52	4.58	2.39
DEF			0.01		0.03	0.03			-0.01		0.03	0.04			0.04	0.04
t-FM			1.17		3.30	3.81			-0.91		3.99	5.20			4.77	4.38
t-GMM			1.16		2.88	3.50			-0.68		3.58	4.93			4.76	3.84
TERM			-0.23		0.05	0.04			-0.13		0.05	0.03			0.05	0.04
t-FM			-4.15		2.11	1.61			-3.91		1.98	1.29			1.70	1.58
t-GMM			-3.14		2.11	1.61			-3.53		1.98	1.27			1.70	1.57
Market		0.00	0.02			-0.17		0.09	0.08			-0.22		0.00		-0.02
t-FM		0.01	0.36			-3.01		2.81	1.79			-3.78		-0.13		-0.53
t-GMM		0.01	0.36			-2.39		2.00	1.55			-2.74		-0.13		-0.49
Intercept	-0.02	0.04	0.01	0.05	0.05	0.05	0.04	-0.09	-0.05	0.05	0.06	0.06	0.05	0.05	0.04	0.06
t-FM	-0.73	0.92	0.26	6.61	6.75	6.63	0.98	-3.19	-1.68	7.32	6.91	7.09	2.48	6.94	2.38	7.31
t-GMM	-0.73	0.92	0.26	6.61	6.75	6.63	0.98	-3.19	-1.68	7.32	6.91	7.09	2.48	6.94	2.38	7.31
AdjR^2	0.13	0.23	0.66	0.09	0.29	0.34	0.28	0.52	0.61	0.05	0.29	0.36	0.06	0.33	0.25	0.50
MAPE %	2.59	2.42	1.07	6.18	5.12	4.83	2.31	1.27	0.99	6.99	4.79	4.11	4.67	4.65	3.35	3.70
Assets	25	25	25	25	25	25	25	25	25	25	25	25	50	50	50	50
Quarters	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26	26

Table 6: GRS Test for LMP Time-series Alpha
This table presents GRS tests on time series alphas generated by each factor model for portfolios consisting of 6 stock portfolios, 1 momentum portfolio, and 6 bond portfolios. 6 stock portfolios are 2 size portfolios and 3 book-to-market-ratio portfolios. 6 bond portfolios are sorted by maturity and credit spreads. The monthly series LMP-TS, LMP-TB, and LMP-TA are calculated by (4.4), (4.5) and (4.6), respectively. GRS F-statistics and p-value are reported in each model in each asset class. Data are quarterly 2010M4:2016M6.

	Stock			Bond		All	
LMP-TS	3.57						
FF3F		3.76					
FF3F+Mom			3.08				
LMP-TB				4.30			
DEF+TERM					4.16		
LMP-TA						4.57	
FF3F+Mom+DEF+TERM							3.39
p-value	0.03	0.01	0.02	0.02	0.02	0.01	0.01

Table 7: This table gives the leverage amplification multiplier n according to (4.7) in three asset classes: stock, bond and all. Investor's leverage parameter $L = 2$ that is roughly equal to the averaged trust stock leverage minus one. The risk-free rate $R_f = 2.7\%$ and the expected WMPs return $\tilde{R}_w = 4.3\%$. The expected market return R_m on stock, bond and all are 7.2%, 4.9% and 5.8%; its standard deviation on stock, bond and all are 0.21, 0.17 and 0.14. The product of the risk premium and the risk exposure $\beta_{LevFac}\lambda_{LevFac}$ are 1.3%, 0.6% and 0.4%, respectively. Given these market data, the investor's relative consumption share y, the profit division ruleω, the maximum risk tolerance $\bar{\sigma}$ and the shadow price of constraint ϕ are calibrated in the three asset classes by what is detailed in Section 4.3. All quantities are annualized. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	All
Loss=10%	1.95	1.15	0.85
Loss=20%	3.91	2.30	1.71
Loss=30%	5.86	3.45	2.56

Table 8: Trust Leverage Risk Factor Prediction

This table presents results that the trust leverage factor predicts one quarter ahead expected asset returns on the equally weighted 25 size and book-to-market stock portfolios, equally weighted 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combing stock and bond. Each model is estimated as (4.8) with each leverage factor from three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA. Table report prediction coefficients with t-Hodrick statistics. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	Stock	Bond	Stock and Bond
	(1)	(2)	(3)	(4)	(5)
LevFac-TS	-0.015				
t-Hodrick	-2.93				
LevFac-TB		-0.010			
t-Hodrick		-3.70			
LevFac-TA			-0.010	-0.009	-0.010
t-Hodrick			-2.90	-3.44	-2.42
Intercept	0.04	0.06	0.04	0.06	0.05
t-Hodrick	4.99	7.54	7.97	7.45	7.48
Adj R^2	0.13	0.07	0.12	0.07	0.07
Quarters	25	25	25	25	25

Table 9: Market Specific Factor Comparison

This table compares performance of LevFac-TS and LevFac-TB for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combining stock and bond. Each model is estimated as 3.2 with LevFac-TS or LevFac-TB. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

Panel A: LevFac-TS Factor

	Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LevFac-TS	0.16	0.23	0.21	-0.22	-0.10	-0.09	0.03	0.11	0.04	0.04
t-FM	2.59	4.99	4.55	-3.29	-1.62	-1.56	0.54	2.23	0.78	0.95
t-GMM	2.48	3.85	3.42	-2.56	-1.47	-1.42	0.51	1.88	0.74	0.88
DEF			0.01		0.03	0.03			0.03	0.03
t-FM			0.94		1.71	2.09			2.48	2.48
t-GMM			0.94		1.47	1.85			2.14	2.13
TERM			-0.25		0.06	0.06			0.04	0.04
t-FM			-4.54		2.36	2.16			1.46	1.47
t-GMM			-3.32		2.33	2.15			1.46	1.46
Market		0.01	0.02			-0.07		-0.00		-0.00
t-FM		0.11	0.42			-1.11		-0.05		-0.03
t-GMM		0.10	0.42			-1.05		-0.05		-0.03
Intercept	0.02	0.02	0.01	0.08	0.06	0.06	0.08	0.06	0.04	0.06
t-FM	0.62	0.87	0.21	7.32	6.74	6.79	6.51	6.38	2.04	7.04
t-GMM	0.62	0.87	0.21	7.32	6.74	6.79	6.51	6.38	2.04	7.04
Adj R^2	0.20	0.24	0.57	0.06	0.20	0.25	0.09	0.26	0.22	0.35
MAPE %	2.59	2.57	1.05	7.49	5.95	5.76	5.99	5.32	5.02	5.03
Assets	25	25	25	25	25	25	50	50	50	50
Quarters	26	26	26	26	26	26	26	26	26	26

Panel B: LevFac-TB Factor

	Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LevFac-TB	-0.13	-0.07	-0.05	0.12	0.09	0.14	0.04	0.06	0.04	0.05
t-FM	-2.37	-1.36	-0.99	2.81	2.37	3.49	0.74	1.77	0.88	1.37
t-GMM	-2.23	-1.36	-0.99	2.68	2.32	3.20	0.74	1.77	0.88	1.37
DEF			-0.02		0.03	0.03			0.03	0.03
t-FM			-1.54		3.65	4.26			4.23	4.26
t-GMM			-1.05		3.26	3.94			3.71	3.76
TERM			-0.13		0.05	0.04			0.03	0.03
t-FM			-3.33		1.85	1.42			1.15	1.14
t-GMM			-3.18		1.85	1.41			1.13	1.12
Market		0.10	0.10			-0.16		-0.01		-0.01
t-FM		2.42	2.35			-2.85		-0.19		-0.34
t-GMM		1.85	1.82			-2.29		-0.18		-0.32
Intercept	0.03	0.07	0.07	0.05	0.05	0.05	0.06	0.05	0.04	0.05
t-FM	1.12	3.12	3.09	7.47	6.84	6.84	5.83	7.47	2.45	7.16
t-GMM	1.12	3.12	3.09	7.47	6.84	6.84	5.83	7.47	2.45	7.16
Adj R^2	0.04	0.21	0.36	0.06	0.29	0.34	0.08	0.28	0.24	0.44
MAPE %	3.39	2.97	2.31	6.94	5.18	5.00	6.01	6.05	4.90	4.89
Assets	25	25	25	25	25	25	50	50	50	50
Quarters	26	26	26	26	26	26	26	26	26	26

Table 10: Trust Leverage Risk Factor Performance in FF3F
This table presents the trust leverage prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spread, and 50 asset portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in the asset class specific to leverage factor. Other factors include Fama-French three factors, DEF, and TERM. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	Stock	Bond	All
LevFac-TS	0.23				
t-FM	4.80				
t-GMM	2.87				
LevFac-TB		0.11			
t-FM		2.96			
t-GMM		2.81			
LevFac-TA			0.12	0.12	0.10
t-FM			2.42	4.51	4.05
t-GMM			1.85	3.95	3.69
DEF	-0.01	0.03	-0.01	0.04	0.03
t-FM	-1.65	4.35	-1.67	4.80	3.87
t-GMM	-0.76	3.98	-0.68	4.66	3.58
TERM	-0.12	0.03	-0.09	0.04	0.04
t-FM	-3.91	1.24	-3.14	1.43	1.69
t-GMM	-3.86	1.23	-3.12	1.43	1.69
Market	0.12	-0.13	0.13	-0.14	-0.02
t-FM	2.96	-2.29	3.20	-2.40	-0.59
t-GMM	2.05	-1.94	2.10	-2.02	-0.55
SMB	-0.01	-0.04	0.00	-0.04	-0.02
t-FM	-0.83	-4.57	-0.16	-3.67	-2.44
t-GMM	-0.34	-2.10	-0.05	-1.88	-1.22
HML	0.01	0.05	0.00	0.04	0.03
t-FM	1.15	4.70	0.69	4.07	3.85
t-GMM	0.33	4.70	0.18	4.02	3.33
Intercept	-0.02	0.05	-0.09	0.05	0.05
t-FM	-3.75	6.93	-4.13	6.98	6.65
t-GMM	-3.75	6.93	-4.13	6.98	6.65
Adj R^2	0.77	0.57	0.76	0.57	0.65
MAPE %	0.53	4.64	0.62	4.02	3.28
Assets	25	25	25	25	50
Quarters	26	26	26	26	26

Table 11: Trust Leverage Risk Factor Performance in FF3F and Moment
This table presents the trust leverage prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spread, and 50 asset portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in the asset class specific to leverage factor. Other factors include Fama-French three factors, Mom, DEF, and TERM. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	Stock	Bond	All
LevFac-TS	0.23				
t-FM	5.25				
t-GMM	2.97				
LevFac-TB		0.13			
t-FM		3.52			
t-GMM		3.22			
LevFac-TA			0.11	0.11	0.11
t-FM			2.39	4.79	4.59
t-GMM			1.83	4.15	4.04
DEF	-0.01	0.03	-0.01	0.04	0.03
t-FM	-1.60	4.29	-1.13	4.80	3.92
t-GMM	-0.77	3.93	-0.47	4.66	3.64
TERM	-0.12	0.03	-0.08	0.04	0.04
t-FM	-4.22	1.28	-2.70	1.42	1.71
t-GMM	-4.14	1.27	-2.68	1.42	1.71
Market	0.12	-0.13	0.13	-0.14	-0.02
t-FM	2.95	-2.32	3.18	-2.40	-0.57
t-GMM	2.05	-1.96	2.10	-2.02	-0.53
SMB	-0.01	-0.04	0.00	-0.04	-0.02
t-FM	-0.86	-4.61	-0.21	-3.74	-2.42
t-GMM	-0.35	-2.12	-0.07	-1.89	-1.22
HML	0.01	0.05	0.01	0.04	0.03
t-FM	1.15	4.79	0.84	4.08	3.92
t-GMM	0.33	4.79	0.22	4.04	3.42
MOM	0.04	0.04	0.04	0.01	0.01
t-FM	3.16	2.87	3.43	0.53	1.24
t-GMM	1.31	2.82	1.31	0.45	1.10
Intercept	-0.02	0.05	-0.10	0.05	0.05
t-FM	-3.76	6.87	-4.08	7.01	6.62
t-GMM	-3.76	6.87	-4.08	7.01	6.62
Adj R^2	0.80	0.60	0.80	0.60	0.67
MAPE %	0.53	4.57	0.58	4.00	3.27
Assets	25	25	25	25	50
Quarters	26	26	26	26	26

Table 12: Trust Leverage Risk Factor Performance in FF5F and Moment
This table presents the trust leverage prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spread, and 50 asset portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in the asset class specific to leverage factor. Other factors include Fama-French five factors, Mom, DEF, and TERM. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	Stock	Bond	All
LevFac-TS	0.22				
t-FM	4.81				
t-GMM	2.98				
LevFac-TB		0.07			
t-FM		1.81			
t-GMM		1.79			
LevFac-TA			0.10	0.08	0.06
t-FM			2.34	3.36	2.69
t-GMM			1.80	3.20	2.65
DEF	-0.01	0.03	0.00	0.03	0.03
t-FM	-1.10	4.53	-0.31	4.58	3.82
t-GMM	-0.62	4.45	-0.17	4.51	3.64
TERM	-0.12	0.04	-0.09	0.04	0.05
t-FM	-4.52	1.62	-2.91	1.60	1.98
t-GMM	-4.20	1.62	-2.87	1.60	1.97
Market	0.10	-0.15	0.10	-0.15	-0.01
t-FM	2.47	-2.40	2.40	-2.50	-0.26
t-GMM	1.89	-2.05	1.87	-2.11	-0.25
SMB	-0.01	-0.03	0.00	-0.03	-0.02
t-FM	-1.01	-3.34	-0.59	-3.45	-2.52
t-GMM	-0.52	-1.86	-0.31	-1.90	-1.32
HML	0.01	0.03	0.01	0.03	0.02
t-FM	1.70	3.18	1.54	3.27	3.24
t-GMM	0.57	3.08	0.55	3.20	2.80
RMW	-0.01	0.01	-0.01	0.01	0.00
t-FM	-1.65	1.65	-1.55	1.81	-0.51
t-GMM	-0.49	1.12	-0.49	1.23	-0.21
CMA	0.00	-0.01	0.00	-0.01	0.00
t-FM	1.89	-2.72	1.25	-2.59	-1.99
t-GMM	0.32	-0.90	0.23	-0.84	-0.50
MOM	0.04	0.00	0.04	0.01	0.01
t-FM	3.36	0.09	3.80	0.54	1.10
t-GMM	1.59	0.08	1.78	0.48	0.99
Intercept	-0.02	0.04	-0.07	0.04	0.04
t-FM	-2.97	6.47	-2.87	6.28	5.84
t-GMM	-2.97	6.47	-2.87	6.28	5.84
Adj R^2	0.86	0.68	0.86	0.68	0.73
MAPE %	0.45	3.93	0.44	3.87	2.88
Assets	25	25	25	25	50
Quarters	26	26	26	26	26

Table 13: Trust Leverage Risk Factor Performance in FF5F, Moment, PS Liquidity
This table presents the trust leverage prices of risk for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spread, and 50 asset portfolios combining stock and bond. Each model is estimated as (3.2) with one of three trust leverage factors LevFac-TS, LevFac-TB and LevFac-TA in the asset class specific to leverage factor. Other factors include Fama-French five factors, Mom, Liq, DEF, and TERM. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are quarterly 2010Q2:2016Q2.

	Stock	Bond	Stock	Bond	All
LevFac-TS	0.22				
t-FM	4.89				
t-GMM	3.00				
LevFac-TB		0.08			
t-FM		1.78			
t-GMM		1.76			
LevFac-TA			0.10	0.09	0.06
t-FM			2.20	3.59	2.76
t-GMM			1.77	3.24	2.68
DEF	-0.01	0.03	-0.01	0.03	0.02
t-FM	-1.18	3.86	-0.69	3.57	3.38
t-GMM	-0.65	3.85	-0.38	3.56	3.26
TERM	-0.13	0.07	-0.10	0.07	0.06
t-FM	-4.60	2.77	-3.47	2.66	2.57
t-GMM	-4.27	2.63	-3.37	2.55	2.50
Market	0.10	-0.03	0.10	-0.14	-0.00
t-FM	2.47	-0.49	2.41	-2.32	-0.08
t-GMM	1.89	-0.48	1.87	-2.02	-0.08
SMB	-0.01	-0.02	-0.01	-0.03	-0.01
t-FM	-1.05	-1.74	-1.05	-3.05	-2.02
t-GMM	-0.54	-1.28	-0.55	-1.97	-1.20
HML	0.01	0.00	0.01	0.02	0.01
t-FM	1.75	0.34	1.90	2.11	2.44
t-GMM	0.57	0.29	0.64	2.08	2.06
RMW	-0.01	0.00	-0.01	0.01	-0.00
t-FM	-1.63	0.53	-1.32	1.84	-0.76
t-GMM	-0.48	0.40	-0.40	1.54	-0.36
CMA	0.00	-0.00	0.00	-0.01	-0.00
t-FM	1.94	-0.49	1.50	-1.88	-1.62
t-GMM	0.32	-0.25	0.27	-0.83	-0.48
MOM	0.04	-0.03	0.04	-0.02	0.00
t-FM	3.35	-2.37	3.62	-1.61	0.15
t-GMM	1.58	-1.78	1.71	-1.28	0.13
LIQ	0.06	0.24	0.03	0.18	0.12
t-FM	0.78	2.28	0.40	1.77	1.49
t-GMM	0.74	2.12	0.38	1.70	1.46
Intercept	-0.07	0.03	-0.07	0.03	0.03
t-FM	-2.93	7.16	-2.89	7.03	7.34
t-GMM	-2.93	7.16	-2.89	7.03	7.34
Adj R^2	0.87	0.72	0.87	0.71	0.75
MAPE %	0.45	3.32	0.42	3.58	2.83
Assets	25	25	25	25	50
Quarters	26	26	26	26	26

Table 14: Monthly Trust Leverage Factor Performance

This table presents pricing results for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combining stock and bond. Each model is estimated as 3.2 with the monthly trust leverage factor. The monthly trust leverage factor is derived from monthly data aggregated from the publicly posted trust plans available from www.eastmoney.com. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are monthly 2010M1:2016M6.

	Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LevFac-TA(m)	0.037	0.032	0.051	0.009	0.043	0.041	0.022	0.033	0.031	0.033
t-FM	2.81	2.48	3.39	1.85	3.88	3.64	3.04	3.82	3.51	4.40
t-GMM	2.59	2.38	2.85	1.75	3.81	3.53	3.04	3.79	3.49	4.40
DEF			0.03		0.05	0.06			0.03	0.03
t-FM			1.82		6.56	7.57			5.02	4.64
t-GMM			1.71		6.39	7.46			4.99	4.52
TERM			-0.01		0.01	0.03			0.02	0.03
t-FM			-0.13		0.57	1.07			1.02	1.10
t-GMM			-0.13		0.54	0.99			1.02	1.09
Market		0.02	0.03			-0.05		-0.03		-0.02
t-FM		0.99	1.22			-3.12		-2.45		-1.96
t-GMM		0.85	1.00			-3.10		-1.87		-1.60
Intercept	-0.01	0.03	0.03	0.04	0.04	0.04	0.03	0.05	0.03	0.05
t-FM	-0.84	3.55	3.88	9.07	8.17	8.38	5.14	8.48	4.14	6.81
t-GMM	-0.84	3.55	3.88	9.07	8.17	8.38	5.14	8.48	4.14	6.81
Adj R^2	0.16	0.26	0.38	0.05	0.31	0.36	0.06	0.20	0.26	0.40
MAPE %	0.51	0.41	0.39	7.04	4.40	4.06	4.49	3.80	3.21	2.64
Assets	25	25	25	25	25	25	50	50	50	50
Quarters	78	78	78	78	78	78	78	78	78	78

Table 15: Monthly Trust LMP Factor Performance
This table presents pricing results for the 25 size and book-to-market stock portfolios, 25 bond portfolios sorted by maturity and credit spreads, and 50 portfolios combining stock and bond. Each model is estimated as (3.2) with the monthly trust LMP factor. The monthly trust LMP factor is the projection of the monthly trust leverage factor on the basis asset returns according to to (4.4), (4.5) and (4.6). The monthly trust leverage factor is derived from monthly data aggregated from publicly posted trust plans available from www.eastmoney.com. Other factors include Market - the stock market factor that is the equity market portfolio return net 1 year risk-free rate, DEF - the credit risk factor that is the market index return of corporate bonds net 10 years government bond return, TERM - the bond market factor that is the 10 years government bond return net 1 year risk-free rate. Table report prices of risk with Fama-Macbeth and GMM t-statistics. Data are monthly 2010M4:2016M6.

	Stock			Bond			All			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LMP-TA(m)	0.009	0.014	0.014	0.010	0.012	0.012	0.008	0.011	0.009	0.011
t-FM	2.26	3.14	3.15	6.08	6.91	6.88	4.87	6.44	5.62	6.71
t-GMM	2.23	3.38	3.33	1.77	2.13	2.04	2.51	1.99	3.15	2.40
DEF			0.03		0.05	0.05			0.04	0.04
t-FM			2.34		6.88	7.25			6.69	6.46
t-GMM			2.13		6.81	7.20			6.52	6.40
TERM			-0.04		0.00	0.01			0.01	0.01
t-FM			-0.76		0.11	0.39			0.56	0.49
t-GMM			-0.73		0.11	0.38			0.55	0.49
Market		0.03	0.04			-0.03		-0.03		-0.02
t-FM		3.02	3.53			-1.91		-2.61		-2.09
t-GMM		2.31	2.52			-1.87		-1.93		-1.64
Intercept	0.01	0.04	0.04	0.06	0.06	0.06	0.03	0.04	0.03	0.05
t-FM	1.05	4.45	5.25	8.97	7.70	7.72	4.89	8.91	4.34	7.45
t-GMM	1.05	4.45	5.25	8.97	7.70	7.72	4.89	8.91	4.34	7.45
Adj R^2	0.11	0.25	0.39	0.09	0.34	0.39	0.07	0.22	0.28	0.43
MAPE %	0.69	0.52	0.48	6.33	3.83	3.68	4.37	3.42	3.13	2.35
Assets	25	25	25	25	25	25	50	50	50	50
Quarters	78	78	78	78	78	78	78	78	78	78