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Essays on Financial Economics

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Essays on Financial Economics

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Economics
2017

Abstract

Essays on Financial Economics
By Jue Ren

The dissertation consists of three essays that study the behavior of financial intermediaries. The first and third essays focus on the mutual fund performance evaluation. The second essay studies the risk-taking behavior of Chinese commercial banks.

The first essay, “Mutual Fund Style Analysis: A Stochastic Dominance Approach,” uses the stochastic dominance test proposed by Linton, Maasoumi, and Whang (2005) to shed new light on mutual fund performance on average and across styles. While most previous research concludes that actively managed mutual funds underperform the market based on the first two moments of mutual fund returns, the first essay asks whether some omitted risk factors or investors’ preferences explain the puzzle. Using the stochastic dominance test, I find little evidence that actively managed mutual funds on average underperform the passive benchmark, suggesting that mutual fund performance results are highly sensitive to investor preference assumptions.

In the second essay, “What Do We Learn from China’s Rising Shadow Banking: Exploring the Nexus of Monetary Tightening and Banks' Role in Entrusted Lending,” I construct a comprehensive transaction-based loan dataset and establish evidence that the rise in China’s shadow banking is inextricably linked to potential balance-sheet risks in the banking system. The empirical and theoretical findings demonstrate that the loans to deposits regulation, coupled with regulations prohibiting banks from making traditional loans to risky industries, creates an incentive for small banks to bring the risk of shadow loans into their balance sheet through regulatory arbitrage in order to compensate for the high costs of meeting random deposit shortfalls.

The third essay, “Measuring Mutual Fund Skill with Active Alphas” examines the impact of beta exposure on mutual fund performance. Similar to the findings in Frazzini and Pedersen (2014), I document that high market beta exposure is associated with low mutual fund standard alpha.
However, when I explore the relationship between mutual fund beta and active alpha, a measure that I define as the difference between a mutual fund’s standard alpha and the matching stock alpha, I find that the active alphas monotonically increase in beta. After adjusting mutual fund returns by a passive stock benchmark, the high beta mutual funds appear to have more skills.

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Preface

The dissertation consists of three essays that study the behavior of financial intermediaries. The first and third essays focus on the mutual fund performance evaluation. The second essay studies the risk-taking behavior of Chinese commercial banks.

The first essay, "Mutual Fund Style Analysis: A Stochastic Dominance Approach," uses the stochastic dominance test proposed by Linton, Maasoumi, and Whang (2005) to shed new light on mutual fund performance on average and across styles. Mutual funds are one of the fastest growing financial intermediaries in the United States. However, academics find that the growth in actively managed U.S. equity mutual funds is puzzling since numerous studies have shown that these funds provide investors with average returns significantly below those of passive benchmarks.

While most previous research concludes that actively managed mutual funds underperform the market based on the first two moments of mutual fund returns, the first essay asks whether some omitted risk factors or investors' preferences explain the puzzle. To address this question, I evaluate mutual fund performance using a non-parametric framework that 1) imposes a minimal set of conditions on preferences; and 2) analyzes the entire return distribution for each mutual fund group. Using the stochastic dominance test, I find little evidence that actively managed mutual funds on average underperform the passive benchmark, suggesting that mutual fund performance results are highly sensitive to investor preference assumptions. Furthermore, I find that mutual fund portfolios formed by the stochastic dominance approach provide superior future performance.

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The third essay, "Measuring Mutual Fund Skill with Active Alphas" examines the impact of beta exposure on mutual fund performance. Similar to the findings in Frazzini and Pedersen (2014), I document that high market beta exposure is associated with low mutual fund standard alpha. However, the standard alphas do not truly measure the skill of managers because the mutual fund stock holdings have different alpha levels. I construct an active alpha measure that adjusts the standard alpha according to a passive benchmark. The benchmark is an equal weighted portfolio of stocks that match the mutual fund holding based market beta. Next, I explore the relationship between mutual fund betas and active alphas. I document that the active alphas almost monotonically increase in beta. After adjusting mutual fund returns by a passive stock benchmark, the high beta mutual funds appear to have more skills.

Chapter I

Mutual Fund Style Analysis: A Stochastic Dominance Approach

Abstract

It is a well-known fact that actively managed mutual funds on average underperform passive benchmarks. In this paper, we use the stochastic dominance test proposed by Linton, Maasoumi, and Whang (2005) to shed new light on mutual fund performance on average and across styles. This test evaluates mutual fund performance using a non-parametric framework that 1) imposes a minimal set of conditions on preferences; and 2) analyzes the entire return distribution for each mutual fund group. We find little evidence that actively managed mutual funds on average underperform the passive benchmark, suggesting that mutual fund performance results are highly sensitive to investor preference assumptions. Exploring the returns for different styles of mutual funds, we find that aggressive mutual funds underperform the market for risk-averse investors, whereas both growth & income and income funds outperform the market for prudent investors. Furthermore, we find that mutual fund portfolios formed by the stochastic dominance approach provide superior future performance.

Key Words: Mutual Fund, Stochastic Dominance, Performance Evaluation

JEL Classification: C12,C15,G11

1.1 Introduction

Mutual funds are one of the fastest growing financial intermediaries in the United States. The industry has grown in size to 16 trillion dollars and attracts over 40 percent of U.S. households as investors. It is the second largest type of financial intermediary in the United States, falling just short of commercial banks.[1] However, there has been a debate about whether or not actively managed mutual fund managers add value. The answer to this questions is crucial for investors' asset allocation decisions and asset managers' investment strategies. Academics find that the growth in actively managed U.S. equity mutual funds is puzzling since numerous studies have shown that, post fees, these funds provide investors with average returns significantly below those on passive benchmarks.[2] While most previous research concludes that actively managed mutual funds underperform the market when comparing the mean and standard deviation of returns, this paper asks two questions: 1) Can some omitted risk factors or investors' preferences explain the puzzle? 2) Do some styles of actively managed mutual funds perform better than others or better than the market?

Investors and academic researchers have a long-standing interest in return and risk tradeoff. The Sharpe ratio, which is defined as the ratio of excess return to volatility, is one of the most common measures of portfolio performance. Sharpe (1966) developed it as a tool for mutual fund performance evaluation. However, Goetzmann, Ingersoll, and Spiegel (2007) point out that a dynamic levering strategy,

[1]See the 2015 Investment Company Fact Book at https://www.ici.org/pdf/2015_factbook.pdf.

[2]See for example, Jensen (1968), Lehmann and Modest (1987), Grinblatt and Titman (1989, 1993), Elton, Gruber, Das, and Hlavka (1993), Brown and Goetzmann (1995), Malkiel (1995), Gruber (1996), Carhart (1997), Edelen (1999), Wermers (2000), Pastor and Stambaugh (2002), Gil-Bazo and Ruiz-Verdu (2009), Fama and French (2010), Elton, Gruber, and Blake (1996, 2003, 2011), and others.

which involves increasing leverage after a period of poor returns or decreasing leverage after a period of good returns, could increase the Sharpe ratio. The manipulation of the Sharpe ratio consists largely in selling the upside return potential, thus creating a distribution with high left-tail risk. A significant restriction on the applicability of the Sharpe ratio results from the facts that: 1) It assumes a quadratic utility function; and 2) It utilizes only the first two moments of the return distributions. When the underlying data appear to follow a normal distribution, quadratic preferences will not miss anything by only considering mean and variance. However, it is well-known that the distributions of financial returns deviate significantly from normality.[3] Thus, variance is inadequate as the only quantifier of risk in mutual fund performance evaluation.

High distribution moments have received notable attention after the recent financial turmoil. A growing body of research reveals that investors favor right skewness,[4] and do not like tail risk or rare disaster risk.[5] Sortino and Price (1994), Dowd (2000), and Kadan and Liu (2014) propose performance measures that account for the higher moments of the distribution. In this paper, we study a performance measure that not only accounts for higher moments of the distribution but also imposes a minimal set of conditions on investors' preferences.

This paper uses a stochastic dominance (SD) approach to test if mutual funds on average underperform as a group and if particular styles of mutual funds underperform. The main advantages of the stochastic dominance approach are that it imposes a minimal set of conditions on investors' preferences and the underlying return distributions. These conditions consist of degree of risk aversion, preference for skewness,

[3]For example, Mandelbrot (1963) and Breen and Savage (1968) have shown that stock price changes are inconsistent with the assumption of normal probability distributions.

[4]See for example, Kraus and Litzenberger (1976), Jean (1971), Kane (1982), Harvey and Siddique (2000), Zhang (2005), Smith (2007), Brunnermeier, Gollier, and Parker (2007), Boyer, Mitton, and Vorkink (2010), Kumar (2009), and others.

[5]See for example, Barro (2009), Gabaix (2008), Gourio (2012), Chen, Joslin, and Tran (2012), Wachter (2013), and others.

and an aversion to kurtosis. For a rational agent with a known utility function, one group of mutual funds is preferred if it maximizes expected utility, which works in theory. However, in practice it is often difficult to find an investor's utility function. Therefore, it would be most useful to know whether or not a certain group of mutual funds is the dominant choice because it is preferred by all agents whose utility functions share certain general characteristics.

To implement the stochastic dominance approach, we examine various levels of stochastic dominance between the returns on mutual fund groups and the passive benchmark. The rules for first order stochastic dominance (FSD) state the necessary and sufficient conditions under which one asset is preferred to another by all expected utility maximizers. The rules for second order stochastic dominance (SSD) state the necessary and sufficient conditions under which one asset is preferred to another by all risk-averse expected utility maximizers. The rules for third order stochastic dominance (TSD) state the necessary and sufficient conditions under which one asset is preferred to another by all prudent (increasing risk aversion) risk-averse expected utility maximizers. If there is no dominance relationship between different classes of mutual funds and the passive benchmark, it suggests that investors with different utility functions will have different preferences over mutual funds and the passive benchmark. If the passive benchmark was to dominate certain mutual fund groups at the first order (or second order), it would mean that all expected utility maximizers (risk-averse investors) prefer the passive benchmark to certain classes of mutual funds. This outcome would be quite puzzling. Why would investors continue to pour money into actively managed funds despite the fact that they prefer the distribution of the passive benchmark?

Using a stochastic dominance approach, which imposes a minimal set of conditions on investors' preferences and the underlying return distributions, we find little evidence that actively managed mutual funds on average underperform the passive benchmark. Although aggressive mutual funds underperform the market for risk-averse investors, there is some evidence showing that both growth & income as well as income funds outperform the market for prudent investors. These results indicate the importance of considering investors' utility functions when analyzing investor behavior.

To implement the stochastic dominance approach, we first compare the return distributions between the mutual funds and the passive benchmark. We adopt value-weighted returns of all stocks listed on the NYSE, AMEX, or NASDAQ (market) as the passive benchmark for comparison. Over the period of 1980 to 2015, there is no evidence of a first order stochastic dominance relationship between the mutual funds and the market. This indicates that expected utility maximizers do not all prefer either mutual funds or the passive benchmark. Similarly, there is no evidence of a second order or third order stochastic dominance relationship between the mutual funds and the market. These results show that there is no uniform preference between the mutual funds and the market for all risk-averse investors nor for all prudent investors as well.

Second, we examine whether some styles of mutual funds perform better than others or than the market. Mutual funds attempt to differentiate their services by specializing in certain sectors of the stock market. Chen, Jegadeesh, and Wermers (2000) point out that growth funds claim to specialize in the "glamour" or low book-to-market stocks, while income funds claim to specialize in "value" or high book-to-market stocks. We analyze whether such specialization adds value to investors and whether some styles of actively managed mutual funds perform better than others or better than the market. We analyze the return distribution of four classes of mutual fund investment objectives (aggressive, growth, growth & income, and income). After deducting management fees, we find that the market dominates the aggressive fund by second order stochastic dominance from 1980 to 2015. This suggests that all risk-averse investors prefer the market over average aggressive funds. The result confirms that it is indeed puzzling why risk-averse individuals would invest in aggressive funds. However, it is possible that the major flow to aggressive funds is made by investors with certain non-concave utility functions.

Surprisingly, there is some evidence showing that both income and growth & income funds dominate the market by third order dominance before and also after fees are deducted. In addition, the SD results show that income and growth & income funds dominate the market by second order dominance during economic recessions. This result is consistent with the findings in Moskowitz (2000), Kosowski (2006) and Glode (2011): active mutual funds perform better in recessions and are therefore potentially desirable relative to passive benchmarks.

Third, we calculate the risk adjusted return based on a four-factor model in order to further compare the performance among different classes of mutual funds. Using a four-factor model, a number of previous studies document that the typical actively managed U.S. equity fund earns a negative alpha after fees (Gruber (1996), Carhart (1997), French (2008), and Fama and French (2010)). We confirm this finding in our risk adjusted return estimation as well. After controlling for the market risk premium, size, value, and momentum factors, the risk adjusted return of aggressive funds is dominated by all of the other three classes of mutual funds by second order stochastic dominance. In addition, growth & income funds dominate all of the other three classes of mutual funds by second order stochastic dominance.

Overall, our results indicate that SD tests provide a robust analysis of mutual fund performance. From a broader perspective, there are two important issues for investors to consider when selecting mutual funds: whether a superior mutual fund can be identified in advance and whether there is persistence in performance. A number of empirical studies demonstrate that the relative performance of equity mutual funds persists from period to period.[6]

Finally, we examine whether ex-post SD relationships provide exploitable information on ex-ante returns. We construct mutual fund portfolios based on second order stochastic dominance. At the beginning of each year between 1995-2015, we identify the dominated (second order) mutual funds based on the most recent sixty monthly returns. We then form an equal weighted portfolio of these dominated mutual funds, which is rebalanced annually. The results show that portfolios formed by a stochastic dominance approach deliver better performance than mean-variance efficient portfolios.

Although a number of studies have used a stochastic dominance approach to rank return distributions in the finance literature, most of these SD tests do not take the dependence structure of financial returns into account. Lean, Phoon, and Wong (2011) employ a stochastic dominance approach to rank the performance of commodity trading advisers' funds. Seyhun (1993) uses a stochastic dominance approach to test for the existence of the January effect. The critical value of stochastic dominance tests in these two studies require an i.i.d assumption for returns. However, Fung and Hsieh (1997) and Brown and Goetzmann (1995) show mutual fund returns are highly correlated and this cross-fund correlation issue should be addressed. In this paper, we have adopted the Linton, Maasoumi, and Whang (LMW) test, which can accommodate not only the general dependence between mutual fund returns, but also the serial dependence.

We describe our data in detail in Section II. Section III introduces the stochastic dominance test, and Section IV discusses the hypotheses and test statistics. Empirical results are provided in Section V and Section VI concludes.

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[6] Carhart (1997), Brown and Goetzmann (1995), Busse and Irvine (2006), and Elton, Gruber, and Blake (1996, 2011).

1.2 Data

Our sample builds upon two data sets. We begin with a mutual fund sample from the CRSP (Center for Research in Security Prices) Survivorship-Bias-Free Mutual Funds database. The database includes information on funds' returns, fees, investment objectives (style), and size (total net assets). In this study, we limit our analysis to actively managed domestic equity mutual funds between March 1980 and December 2015, which contains the most complete and reliable return data.[7] Specifically, we include only mutual funds that have a self-declared investment objective of "MCG," "AGG," "CA," "G," "LTG," "GRO," "IEQ," "OPI," "EI," "GCI," "GRI," or "GI."

We follow Kacperczyk, Sialm, and Zheng (2008) in eliminating balanced, bond, money market, international, sector, and index funds. We mainly use CRSP objective codes to classify the mutual funds into four investment classes (aggressive, growth, growth & income, and income). As shown in Table 1, we classify mutual funds with the objective of "Maximum Capital Gains," "Equity USA Aggressive Growth," or "Capital Appreciation Funds" as aggressive funds; mutual funds with the objective of "Growth," "Long-Term Growth," or "Equity USA Growth" as growth funds; mutual funds with the objective of "Equity Income," "Option Income," or "Equity Income Funds" as income funds; and mutual funds with the objective of "Growth and Current Income," "Equity USA growth & income," "Equity USA Income &Growth," or "Growth and Income Funds" as growth & income funds.

Some mutual funds have multiple share classes. The CRSP data lists each share class as a separate fund. Different share classes have the same holding compositions and typically differ only in fee structure. The returns histories are therefore sometimes

[7] Fama and French (2010) state that there is a potential problem in the CRSP mutual fund return data during the period 1962 to 1983. For this time period, about 15% of the funds on the CRSP report only annual returns, and the average annual equal-weight (EW) return for these funds is 5.29% lower than for funds that report monthly returns. Also, MFLINKS data starts in March 1980. Given the nature of our tests and data availability, we choose the sample period from March 1980 to December 2015.

duplicated in the CRSP dataset. For example, if a fund started in 1983 and split into four share classes in 1993, each new share class of the fund is permitted to inherit the entire return history. This can create a bias when averaging returns across mutual funds. For funds with multiple share classes, we use the identification code in MFLINKS to combine different classes of the same fund into a single value-weighted fund. Wermers (2000) provides a description of how MFLINKS are created. Each monthly fund return is computed by weighting the return of its component share classes by their beginning-of-month total net asset values.

We obtain monthly data for the size, value, momentum, and market portfolios for the period of 1980 to 2015 from Kenneth French's data library. We measure recessions using the definition of the National Bureau of Economic Research (NBER) business cycle dating committee. The start of the recession is the peak of economic activity and its end is the trough. Our aggregate sample spans 430 months of data from March 1980 until December 2015, among which 55 are NBER recession months (13%).

1.3 Stochastic Dominance

This section provides a non-parametric approach based on stochastic dominance testing to evaluate mutual fund performance. The theory of stochastic dominance offers a decision-making rule under uncertainty provided the decision maker's utility function has certain properties. The different orders of stochastic dominance correspond to increasing restrictions on the shape of the utility function and the agents' attitude towards higher order moments. These restrictions are non-parametric and do not require specific parametric function forms.

We first briefly define the criteria of stochastic dominance:

1. First order stochastic dominance: When A dominates B by first order stochastic dominance, all expected utility maximizers ($u' \geq 0$) prefer A to B.

2. Second order stochastic dominance: When A dominates B by second order stochastic dominance, all risk-averse expected utility maximizers ($u' \geq 0,\ u'' \leq 0$) prefer A to B.

3. Third order stochastic dominance: When A dominates B by third order stochastic dominance, all prudent risk-averse expected utility maximizers ($u' \geq 0,\ u'' \leq 0,\ u''' \geq 0$) prefer A to B.

We use X_1 and X_2 to denote two random variables (e.g., mutual fund returns and market returns). Let U_1 denote the set of von Neumann-Morgenstern type utility functions, u, such that $u' \geq 0$ (more is better than less). Let U_2 denote the set of utility functions in U_1 for which $u'' \leq 0$ (concavity). Let U_3 denote the class of all utility functions in U_2 for which $u''' \geq 0$ (increasing risk aversion). Let $F_1(x)$ and $F_2(x)$ be the cumulative distribution functions, respectively.

Then define the following:

Definition 1: X_1 first order stochastic dominates X_2, denoted $X_1 \succeq_{FSD} X_2$, if and only if:

$E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_1$ with strict inequality for some u; or

$F_1(x) \leq F_2(x)$ for all x with strict inequality for some x.

Definition 2: X_1 second order stochastic dominates X_2, denoted $X_1 \succeq_{SSD} X_2$, if and only if:

$E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_2$ with strict inequality for some u; or

$\int_{-\infty}^{x} F_1(t)dt \leq \int_{-\infty}^{x} F_2(t)dt$ for all x with strict inequality for some x.

Definition 3: X_1 third order stochastic dominates X_2, denoted $X_1 \succeq_{TSD} X_2$, if and only if:

$E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_3$ with strict inequality for some u; or

$\int_{-\infty}^{x} \int_{-\infty}^{z} F_1(t)dtdz \leq \int_{-\infty}^{x} \int_{-\infty}^{z} F_2(t)dtdz$ for all x with strict inequality for some x.

Mathematically, lower order dominance implies all higher order dominance rankings. In the case of first order dominance, the distribution function of X_1 lies everywhere to the right of the distribution function of X_2 except for a finite number of points where there is strict equality. For first order stochastic dominance, the probability that returns of X_1 are in excess of r is higher than the corresponding probability associated with X_2.

$$Pr(X_1 > r) \geq Pr(X_2 > r).$$

An important feature of the definitions of stochastic dominance is that they impose minimum conditions on the preferences of agents within the class of von Neumann–Morgenstern utility functions. Stochastic dominance is more satisfactory than the commonly used mean-variance rule since it is defined with reference to a much larger class of utility functions and return distributions. Levy (2006) provides an example showing that the mean-variance approach produces an inaccurate evaluation result. Suppose that $X_1 \in \{1, 2\}$ has equal probability on each outcome and that $X_1 \in \{2, 4\}$ also has equal probability on each outcome. Then $E(X_1) < E(X_2)$, but $var(X_1) < var(X_2)$, so that there exists a mean-variance optimizer who prefers X_1 over X_2. However, this does not make economic sense because $X_1 \leq X_2$ with a probability of one. X_1 is first order stochastic dominated by X_2.

1.4 Hypotheses and Test Statistics

X_1 denotes the average actively managed mutual fund return; X_2 denotes the market return; X_3 denotes the aggressive fund return; X_4 denotes growth fund return; X_5 denotes growth and income fund return; and X_6 denotes income fund return. The hypothesis tested is whether or not one group of mutual funds or the market dominates the other. We examine the stochastic dominance relationship between all pairs of returns of X_k for $k = 1 \ldots 6$. One example of the type of test we conduct is:

H_0: The market stochastically dominates average actively managed mutual fund, with the alternative being that there is no stochastic dominance.

Next, we formalize these tests. Let χ denote the support of X_k for $k = 1 \ldots 6$ and let $s = 1,\ 2,\ 3$ represent the order of stochastic dominance. Define:

$$F_K(x) = P(X \leq x), \tag{1.1}$$

$$D_K^{(1)}(x) = F_K(x), \tag{1.2}$$

$$D_K^{(s)}(x) = \int_{-\infty}^{x} D_K^{(s-1)}(t)dt \ for \ s \geq 2. \tag{1.3}$$

We say that X_k stochastically dominates X_l at order s, if $D_k^{(s)}(x) \leq D_l^{(s)}(x)$ for all x with strict inequality for some x.

For each $k = 1 \ldots 6$; $s = 1,\ 2,\ 3$, and $x \in \chi$, let $D_{kl}^{(s)} = D_k^{(s)}(x) - D_l^{(s)}(x)$. Define:

$$d_s^* = max_{k \neq l} sup_{x \in \chi} \left[D_{kl}^{(s)} \right]. \tag{1.4}$$

As Klecan, McFadden, and McFadden (1991) suggests, the hypothesis of interest can be stated as:

$$H_0 : d_s^* \leq 0 \ vs. \ H_a : d_s^* > 0. \tag{1.5}$$

The test statistics are based on the empirical analogues of d_s^*. We define the test statistics as:

$$D_N^{(s)} = max_{k \neq l} sup_{x \in \mathcal{X}} \sqrt{N} \left[\bar{D}_{kl}^{(s)}(x) \right], \tag{1.6}$$

where

$$\bar{D}_k^{(s)}(x) = \frac{1}{N(S-1)!} \sum_{i=1}^{N} (x - X_{ki})^{s-1} 1(X_{ki} \leq x) \ for \ k = 1, ..., 6. \tag{1.7}$$

We adopt a recentering function to account for the effect of the parameter estimation error as suggested in Donald and Hsu (2013). Simulation results in Donald and Hsu (2013) show that the recentering function increases the power of the test. For a given small negative number a_N, define the recentering function as $\mu = (\hat{F}_k(x) - \hat{F}_l(x)) * 1(\sqrt{N}(\hat{F}_k(x) - \hat{F}_l(x)) < a_{N.}$

We next describe the main method for obtaining critical values: the subsampling approach. Klecan, McFadden, and McFadden (1991) point out that even when the data are i.i.d in stochastic dominance testing, the standard bootstrap method does not work because one needs to impose the null hypothesis in that case. The mutual dependence of the fund returns as well as the time series dependence in the data make it challenging to obtain consistent critical values. As Linton, Maasoumi, and Whang (2005) suggest, we use the subsampling method to obtain a consistent critical value.

In order to define the subsampling procedure, let $W_i = \{X_{ki} : \ k = 1, 2, 3, 4, 5, 6\}$for $i = 1...N$. T_N denotes the test statistics $D_N^{(s)}$. We first generate the subsamples of size b by taking without replacement from the original data. There will be $N-b+1$ different subsamples of size b. We then compute the test statistics $t_{N,b,i}$ using subsamples $\{W_i, W_{i+1}, \ldots, W_{i+b-1}\}$ for $i = 1, 2, ..., N-b+1$. Linton, Maasoumi, and Whang (2005) show that this subsampling procedure works under a very weak condition on b and is data-dependent. The sampling distribution G_N of T_N can be approximated by:

$$G_{N,b}(w) = \frac{1}{N-b+1} \sum_{i=1}^{N-b+1} 1(\sqrt{b}t_{N,b,i} \leq w). \tag{1.8}$$

$g_{N.b}(1-\alpha)$ is the $(1-\alpha)$th sample quantile of $G_{N,b}(w)$. We reject the null at significant level α if $T_n > g_{N.b}(1-\alpha)$.

1.5 Results

1.5.1 Summary Data on Mutual Funds

Table 2 reports the summary statistics for our actively managed mutual fund sample. There are a total of 2,666 mutual funds in our sample, which are divided into four categories as previously discussed. Aggressive funds attempt to achieve the highest capital gains and the investments held in these funds are companies that demonstrate high growth potential, usually accompanied by a large amount of share price volatility. Growth funds invest in growth companies with the primary aim of achieving capital gains instead of dividend income. Income funds seek to provide a high current income by investing in high-yielding conservative stocks. Growth & income funds seek to provide both capital gains and a steady stream of income. In Panel A, we report the gross returns, net returns, skewness, kurtosis, autocorrelation, and Sharpe ratio for equal weighted mutual fund groups. Gross return is defined as the mutual funds' return before deducting any management fees. Net return is the return received by investors. Consistent with what the previous literature has found, the average returns of all five mutual fund groups are lower than the market. The standard deviation for more conservative funds is lower. All mutual fund groups' return and the market return are negatively skewed. All the returns series have some serial dependence based on the autocorrelation statistics. In Panel B, we report similar statistics for value-weighted mutual fund groups. Panel C shows that all of the returns of the mutual fund groups are highly correlated. Thus, the LMW stochastic dominance test is used because it accommodates not only general dependence between returns, but also serial dependence.

1.5.2 Normality Test

When the underlying variable is normal, the traditional performance evaluation measure will not miss anything by only considering mean and variance. However, one issue in performance evaluation is that the returns of mutual funds are non-normal. Table 3 shows the Kolmogorov-Smirnov and Jarque-Bera test results. For any group of mutual funds, the normality hypothesis is strongly rejected. Previous literature has also documented non-normalities in mutual fund returns. Kosowski, Timmermann, Wermers, and White (2006) suggest these non-normalities arise for three reasons. First, individual stocks within a typical mutual fund portfolio realize returns with non-negligible higher moments and managers often hold heavy positions in relatively few stocks or industries. Second, individual stocks exhibit varying levels of time-series autocorrelations in returns. Third, funds may implement dynamic strategies that involve changing their levels of risk-taking when the risk of the overall market portfolio changes. Kosowski, Timmermann, Wermers, and White (2006) argue that normality may be a poor approximation in practice, even for a fairly large mutual fund portfolio. The stochastic dominance test is based on the entire distribution. Unlike the Sharpe ratio, it does not require the return to be normally distributed.

1.5.3 Mutual Funds and Market Return Comparison

Stochastic dominance tests implicitly take into account the differences in expected returns and risk. While traditional performance evaluation tools take the standard deviation as a quantifier for risk, the stochastic dominance approach will consider standard deviation, skewness, kurtosis, and all higher moments for the evaluation. For example, we are interested in comparing asset A and asset B for investors with general utility assumptions. If asset A has a higher expected return than asset B, then asset A will be preferred if we only consider the mean and ignore the risk. However, if the higher expected return of asset A is due to its higher risk, then asset A would exhibit more extreme positive and negative returns. For investors with various preferences for risk and return trade-off, asset A may or may not be preferred. Thus, asset A will not stochastically dominate asset B.

In this section, we apply the stochastic dominance test to compare the distributions of monthly market returns and mutual fund returns. Figure 1 shows the cumulative density function (CDF) of the realized equal weighted actively managed mutual fund returns and market returns from 1980-2015 and Figure 2 shows the CDF of the realized value-weighted actively managed mutual fund returns and market returns for the same time period. Inspection of the graph suggests no evidence of first order stochastic dominance as the two CDFs cross.

Table 4 summarizes the stochastic dominance test results for equal weighted mutual funds and the market. In Panel A, we test for stochastic dominance between the market and mutual fund net returns. In Panel B, we test for stochastic dominance between the market and mutual fund gross returns. The first column of Table 4 lists the return pairs we are testing. The null hypothesis is that the first return series will stochastically dominate the second return series. For example, "Average Mutual Fund vs. Market" means that we test whether or not the equal-weighted average of mutual fund returns stochastically dominate the market. In the second column, we list the order of stochastic dominance being tested. The test statistics are given in the third column. The final three columns provide the p-value calculated from a different subsample block size.

The test statistics of FSD in Panel A of Table 4 has a value of 0.27 with a p-value of 0.00. As expected from Figure 1, the market returns do not dominate the average actively managed fund net returns by first order stochastic dominance. This implies that expected utility maximizers do not all prefer either actively managed mutual funds or the market benchmark. The test value of SSD in Panel A has a value of 0.01, with a p-value of 0.00, showing that there is also no evidence of second order stochastic dominance between the two assets. This implies that risk-averse investors do not all prefer either actively managed mutual funds or the market benchmark. The test value of TSD in Panel A is positive and shows no evidence of third order stochastic dominance between two assets. This implies that prudent investors also do not all prefer either actively managed mutual funds or the market benchmark.

Panel B of Table 4 shows the SD test results for the market and actively managed mutual fund gross returns. Even without deducting any management fees, there is still no evidence of a dominance relationship between two assets. The SD test statistics are all positive with p-values less than 5%.

Overall, the results in Table 4 show no stochastic dominance relationship between average actively managed mutual fund returns and the market returns by first order, second order, or third order stochastic dominance. The SD test statistics are all positive with p-values less than 5%. This suggests that investors with certain utility functions prefer the distribution of the market returns, while some other investors with different utility functions prefer the return distribution of actively managed mutual funds. The test results here reveal that investors' utility functions will play a role in evaluating the return distribution of actively managed funds and the market.

1.5.4 Investment Objective Subgroups of Mutual Funds and Market Return Comparison

Mutual funds have attempted to differentiate their services by specializing in certain sectors of the stock market and adopting various investment styles. For example, growth funds claim to specialize in low book-to-market stocks, while income funds claim to specialize in high book-to-market stocks. The question is whether such specialization adds value to investors. We investigate this issue by partitioning funds based on their self-declared investment objectives (aggressive, growth, income, and growth & income). In this Section, we use a stochastic dominance approach to examine whether some styles of mutual funds perform better than others or better than the market. Figure 2 and Figure 3 plot the CDF of four classes of mutual fund and the market returns. Once again, all of the CDFs cross, so we do not expect to find first order stochastic dominance.

Table 5 summarizes the stochastic dominance results for the four mutual fund classes and the market both before and after management fees have been deducted. Before deducting management fees, aggressive funds are third order stochastically dominated by each of the other three classes of mutual funds and also the market. After deducting management fees, aggressive funds are still third order dominated by each of the other three classes of mutual funds and second order dominated by the market. This test result shows that aggressive funds on average are inferior to the other three mutual fund classes and the market for all prudent investors with or without considering management fees. Also, on a net return basis, all risk-averse investors prefer the market to average aggressive funds. The underperformance of aggressive funds is not surprising given the high exposure to market risk and high betas. Hong and Sraer (2016) provide a theory for why high beta assets are prone to speculative overpricing. They point out that when investors disagree about the stock market's prospects, high beta assets are more sensitive to this aggregate disagreement. Thus, high beta assets experience a greater divergence of opinion about their payoffs and are overpriced due to short-sales constraints. The stochastic test result confirms that risk-averse individuals do not prefer aggressive funds. This suggests that the major flow to aggressive funds is probably made by investors with certain non-concave utility functions.

The absence of second order stochastic dominance between income funds and the market means that certain risk-averse individuals (e.g., those with quadratic utility functions) prefer the income fund, while some other risk-averse individuals with different utility functions prefer the market return. This result is in contrast to the Sharpe ratio result, presented in the summary statistics table, which posits that the income fund (Sharpe ratio 14.26) is preferred to the market (Sharpe ratio 13.98) for all agents with a quadratic utility function. Although the Sharpe ratio also considers this risk and return trade-off with variance as the quantifier for risk, since it ignores higher moments in the distribution, it does not provide an accurate result for all subsets of this data. In counterpoint, the stochastic dominance approach provides a robust analysis of the performance, which allows for differentiation between different types of investors.

Surprisingly, there is some evidence that both growth & income funds and income funds dominate the market by third order stochastic dominance before and also after fees. This implies that income and growth & income will be favored for all prudent individuals who have a preference for positive skewness and an aversion for variance and kurtosis. As shown in the summary statistics, income and growth & income funds have slightly lower average returns than the market. However, they both also have a lower variance, smaller negative skewness, and smaller kurtosis. Including these measures of risk preference will therefore provide a different picture of the fund performance evaluation. Even though these funds have lower returns, they are also less risky. The existence of third order stochastic dominance means that all prudent investors prefer income and growth & income funds to the market as seen in the entire 1980-2015 monthly return distribution.

1.5.5 Recession/Boom

The early literature on the value of active mutual fund management focuses on unconditional return performance and generally finds that the average fund underperforms passive benchmarks[8] and that there is evidence of negative market timing.[9] However, Moskowitz (2000), Kosowski (2006), and Glode (2011) all suggest that unconditional mutual fund performance measures may understate the value of mutual funds to investors since they cannot answer the question of how mutual funds perform in recession states when investors' marginal utility of wealth is highest. Their findings imply that actively managed mutual funds perform better in recessions and are therefore potentially desirable relative to benchmarks. In this Section, we explore the performance of mutual funds and the market during different economics conditions. The stochastic dominance test is conducted for NBER recessions and expansions. Our aggregate sample spans 430 months of data from March 1980 until December 2015, among which 55 are NBER recession months (13%).

During economic expansion periods, the SD test results are very similar to what were seen in previous Sections. First, there is no dominance relationship between average actively managed mutual funds and the market by first order, second order,

[8]See for example, Jensen (1968), Lehmann and Modest (1987), Grinblatt and Titman (1989, 1993), Elton, Gruber, Das, and Hlavka (1993), Brown and Goetzmann (1995), Malkiel (1995), Gruber (1996), Carhart (1997), Edelen (1999), Wermers (2000), Pastor and Stambaugh (2002), Gil-Bazo and Ruiz-Verdu (2009), Fama and French (2010), Elton, Gruber, and Blake (1996, 2003, 2011), and others.

[9] See Treynor and Mazuy (1966), Henriksson and Merton (1981), Chang and Lewellen (1984), Grinblatt and Titman (1989), and Jagannathan and Korajczyk (1986) for (unconditional) market timing studies.

or third order stochastic dominance during the economic expansion periods in our sample. Second, Panel A of Table 6 shows that the market still dominates aggressive funds by second order stochastic dominance after deducting all the fees during economic expansion periods. Also, aggressive funds are third order stochastically dominated by the other three mutual fund classes. Third, there is evidence showing that income and growth & income funds dominate the market by third order dominance during economic expansions.

During economic recession periods, there is no dominance relationship between average actively managed mutual funds and the market by first order, second order, and third order stochastic doninance in our sample. Panel B of Table 6 shows the SD test results for the four styles of mutual funds and the market during economic recession periods. Aggressive funds are not only third order stochastically dominated by the market, but also second order stochastically dominated by income funds and the growth & income funds. This suggests that the underperformance of aggressive funds persist during recessions. Income and growth & income funds dominate the market by second order stochastic dominance. This implies that during recessions, risk-averse investors prefer growth & income funds and income funds to the market. Thus, these funds do create some value for risk-averse investors during economic recession periods.

1.5.6 Risk Adjusted Return

In order to further compare the performance among different classes of mutual funds, we calculate the risk adjusted return based on a four-factor model as proposed in Carhart (1997). The models use the regression framework below:

$$R_{it} - R_{ft} = a_i + b_i(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + m_i MOM_t + e_{it}.$$

In this regression, R_{it} is the return on fund i for month t, R_{ft} is the risk-free rate (the one month U.S. Treasury bill rate), R_{Mt} is the market return (the return on a VW portfolio of NYSE, Amex, and NASDAQ stocks), SMB_t and HML_t are the size and value factors as in Fama and French (1993), MOM_t is Carhart's (1997) momentum factor, a_i is the average return left unexplained by the benchmark model, and e_{it} is the regression residual. Table 7 provides the summary statistics for all of the factors used in the regression and Table 8 shows the regression results. Overall, mutual funds do tilt their investments more toward stocks that match their stated objectives. Aggressive funds have more exposure to all risk factors. It is well-known that aggressive funds tilt toward small capitalization, low book-to-market, and momentum stocks, while the opposite holds true for income funds.

For each fund i, the risk-adjusted return is calculated as:

$$\hat{\alpha}_{it} = R_{it} - \hat{\beta}_i^T Z_t,$$

where $Z_t$is the value of factors at month t.

We next conduct an analysis of the distributions of risk adjusted returns of the mutual funds. Table 9 shows the SD test results for risk adjusted returns based on the four-factor model. After controlling the market risk premium, size, value, and momentum factors, the risk adjusted returns of aggressive funds are dominated by all of the other three classes of mutual funds by second order stochastic dominance. In addition, the risk adjusted returns of growth & income funds dominate all of the other three classes of mutual funds by second order stochastic dominance.

1.6 Investment Strategy

Two important issues for mutual fund investors are whether a superior mutual fund can be identified in advance and whether the superior performance persists. Many studies have found performance persistence in the top-ranked mutual fund groups based on past returns, past alpha, and past Sharpe ratio.[10] In this Section, we use the stochastic dominance relationship as a criterion for portfolio construction. We examine whether ex-post SD relationships provide exploitable information on ex-ante returns. This empirical exercise targets second order stochastic dominance. At the beginning of each year between 1995-2015, we identify the undominated (second order) mutual funds based on the most recent 60-month returns. We then form an equal weighted portfolio of undominated mutual funds. The portfolio is rebalanced annually. For comparison, mean-variance efficient portfolios are formed for the same time period.

Table 10 shows the portfolio performance based on a stochastic dominance approach and a mean-variance approach. The mean return of the portfolio of second order undominated funds is 1.92%, which is substantially larger than the portfolio of first order dominated funds. The average return of the mean-variance efficient portfolio is 1.42%, with a 3.21 standard deviation and negative skewness. The portfolio of second order undominated funds has a smaller standard deviation and positive skewness compared to the mean-variance efficient portfolio. This shows that the stochastic dominance approach may potentially be used for mutual fund selection.

1.7 Robustness

1.7.1 Liquidity Factor

Pástor and Stambaugh (2003) show that expected stock returns are related cross-sectionally to the sensitivities of the returns to fluctuations in aggregate liquidity. We introduce the liquidity factor to capture such an effect, in addition to the market, size, value, and momentum factors. Table 11 shows the SD test results for risk adjusted returns based on a five-factor model. The result is similar to what we have before.

[10] Carhart (1997), Busse and Irvine (2006), and Elton, Gruber, and Blake (1996, 2011).

After controlling for the market risk premium, size, value, momentum, and liquidity factors, the risk adjusted returns of aggressive funds are dominated by all of the other three classes of mutual funds by second order stochastic dominance. Also, the risk adjusted returns of growth & income funds dominate all of the other three classes of mutual funds by second order stochastic dominance.

1.7.2 Value Weighted Portfolios

As a robustness check, we consider if our results are sensitive to the weighting method. We perform all of the analyses again using the value-weighted mutual fund portfolios. Figure 4 plots the CDF of the net and gross return distributions of the market and the value-weighted mutual fund portfolios. As before, the two CDFs cross and we do not expect to find a first order stochastic dominance relationship. Overall, we found the results are very robust to different weighting methods. First, Table 12 shows that there is no stochastic dominance relationship between value-weighted mutual fund portoflios and the market, with or without fees.

Second, the results in Table 13 show that the market still dominates aggressive funds by second order dominance after deducting all fees. Also, aggressive funds are third order stochastically dominated by all of the other three mutual fund classes. Third, there is evidence showing that income and growth & income funds dominate the market by third order dominance, with or without deducting the management fees.

Finally, Table 14 shows the SD test results for value-weighted risk adjusted returns based on four-factor and five factor models. In both cases, the risk adjusted returns of aggressive funds are dominated by all of the other three classes of mutual funds by third order stochastic dominance. In addition, the risk adjusted returns of growth & income funds dominate both growth funds and income funds by second order stochastic dominance.

1.8 Conclusion

Although there is no consensus on investors' utility function form, traditional mutual fund performance evaluation measures usually rely on a quadratic utility assumption. Moreover, even though investors recognize the importance of the higher moments of a return distribution, they generally only use variance as a risk measurement. To address this issue, this paper evaluates mutual fund performance using a non-parametric framework that 1) imposes a minimal set of conditions on preferences; and 2) analyzes the entire return distribution for each mutual fund group. Previous literature finds that actively managed mutual funds on average underperform the passive benchmark by comparing the mean and standard deviation of returns. We revisit the actively managed mutual funds underperformance puzzle by applying the stochastic dominance test proposed by Linton, Maasoumi, and Whang (2005) to verify if actively managed mutual funds on average underperform and if any particular style of actively managed mutual funds (aggressive, growth, growth & income, and income) underperforms. The test results show little evidence that actively managed mutual funds on average underperform the passive benchmark. This suggests that investors with different utility functions will have different preferences over actively managed mutual funds and the passive benchmark. Although aggressive mutual funds underperform the market for risk-averse investors, there is some evidence showing that both growth & income and income funds outperform the market for prudent investors. Furthermore, we find that mutual fund portfolios formed by the stochastic dominance approach provide superior future performance.

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Table 1.1: Mutual Fund Style Classification

The CRSP U.S. Survivor-Bias-Free Mutual Funds database includes style and objective codes from three different sources over the life of the database. No single source exists for its full-time range. Wiesenberger Objective codes are populated between 1962–1993; Strategic Insight Objective codes are populated between 1993–1998; and Lipper Objective codes begin in 1998. We classify mutual funds with the objective of " Maximum Capital Gains," "Equity USA Aggressive Growth," "Capital Appreciation Funds" as aggressive funds. Mutual funds with the objective of "Growth," "Long-Term Growth," and "Equity USA Growth" are growth funds. Mutual funds with the objective of "Equity Income," "Option Income," and "Equity Income Funds" are income funds. Mutual funds with the objective of "Growth and Current Income," "Equity USA growth & income," "Equity USA Income &Growth," and " Growth and Income Funds" are growth & income funds.

	Wiesenberger (1980-1993)	Strategic Insights (1993-1998)	Lipper (After 1998)
Aggressive	MCG Maximum Capital Gains	AGG Equity USA Aggressive Growth	CA Capital Appreciation Funds
Growth	G Growth; LTG Long-Term Growth	GRO Equity USA Growth	G Growth Funds
Income	IEQ Equity Income	OPI Option Income	EI Equity Income Funds
Growth & Income	GCI Growth and Current Income	GRI Equity USA Growth & Income; ING Equity USA Income & Growth	GI Growth and Income Funds

Table 1.2: Summary statistics

This table reports the summary statistics for the funds in our sample. The sample period is March 1980-December 2015. Mutual fund share class level returns are from the CRSP mutual fund database. We combined different classes of the same fund into a single fund using the identification in MFLINKS. Each monthly fund return is computed by weighting the return of its component share classes by their beginning-of-month total net asset values. "Number of funds" is the number of mutual funds that meet our selection criteria for being an active mutual fund and have a self-declared investment objective of "MCG," "AGG," "CA," "G," "LTG," "GRO," "IEQ," "OPI," "EI," "GCI," "GRI," or "GI." Gross return is the mutual fund's return before deducting any management fees. Net return is the return received by investors. Market return (column 7) reports the returns on a VW portfolio of NYSE, Amex, and NASDAQ stocks.

Panel A: EW

	Aggressive	Growth	G&I	Income	All	Market
Gross Return (%/month)	1.05	1.00	0.98	0.96	1.00	1.00
Net Return (%/month)	0.93	0.91	0.90	0.88	0.91	1.00
Standard Deviation	4.93	4.40	3.93	3.58	4.30	4.48
Kurtosis	5.37	5.76	5.29	5.31	5.60	5.33
Skewness	-0.71	-0.83	-0.68	-0.71	-0.81	-0.73
Number of Funds	347	1573	635	111	2666	
Minimum (%/month)	-25.08	-23.13	-19.18	-16.78	-22.65	-22.64
Maximum (%/month)	13.69	11.72	10.65	10.33	11.83	12.89
Autocorrelation	0.13	0.10	0.09	0.10	0.10	0.08
Sharp Ratio	11.37	12.15	13.56	14.26	12.43	13.98

Panel B: VW

	Aggressive	Growth	G&I	Income	All	Market
Gross Return (%/month)	1.07	1.02	0.98	0.98	1.01	1.00
Net Return (%/month)	0.98	0.94	0.93	0.91	0.94	1.00
Standard Deviation	4.92	4.51	3.83	3.79	4.25	4.48
Kurtosis	5.45	5.44	5.29	5.24	5.57	5.33
Skewness	-0.70	-0.75	-0.71	-0.73	-0.76	-0.73
Minimum (%/month)	-24.27	-22.92	-19.25	-18.64	-21.85	-22.64
Maximum (%/month)	15.03	12.42	11.18	10.43	12.04	12.89
Autocorrelation	0.12	0.09	0.07	0.08	0.09	0.08
Sharp Ratio	12.39	12.71	14.59	14.26	13.31	13.98

Panel C: Correlation

	Aggressive	Growth	Growth & Income	Income	Market
Aggressive	1.00				
Growth	0.98	1.00			
Growth & Income	0.93	0.98	1.00		
Income	0.87	0.93	0.98	1.00	
Market	0.96	0.99	0.99	0.95	1.00

Table 1.3: Normality Test for Mutual Fund Returns

This table shows the normality test resultS for mutual fund returns. The sample period is March 1980-December 2015. Mutual fund share class level returns are from the CRSP mutual fund database. We combined different classes of the same fund into a single fund using the identification in MFLINKS, with value weights. The null hypothsis is H_0 : Data follows a normal distribution. The alternative hypothesis is that H_a: Data does not follow a normal distribution. The test results show that the normality assumption is strongly rejected by the test.

	Kolmogorov-Smirnov		Jarque-Bera		
	Test statistics	P value	Pr(skew)	Pr(Kurt)	P value
Aggressive	0.43	0.00	0.00	0.00	0.00
Growth	0.44	0.00	0.00	0.00	0.00
Growth & Income	0.44	0.00	0.00	0.00	0.00
Income	0.42	0.00	0.00	0.00	0.00
All	0.43	0.00	0.00	0.00	0.00

Figure 1.1: CDF of EW Mutual Funds and Market Returns

This figure plots the CDF of EW mutual fund and market returns. In the first Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of EW mutual fund net returns. In the second Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of EW mutual fund gross returns.The sample period is from March 1980 and December 2015.

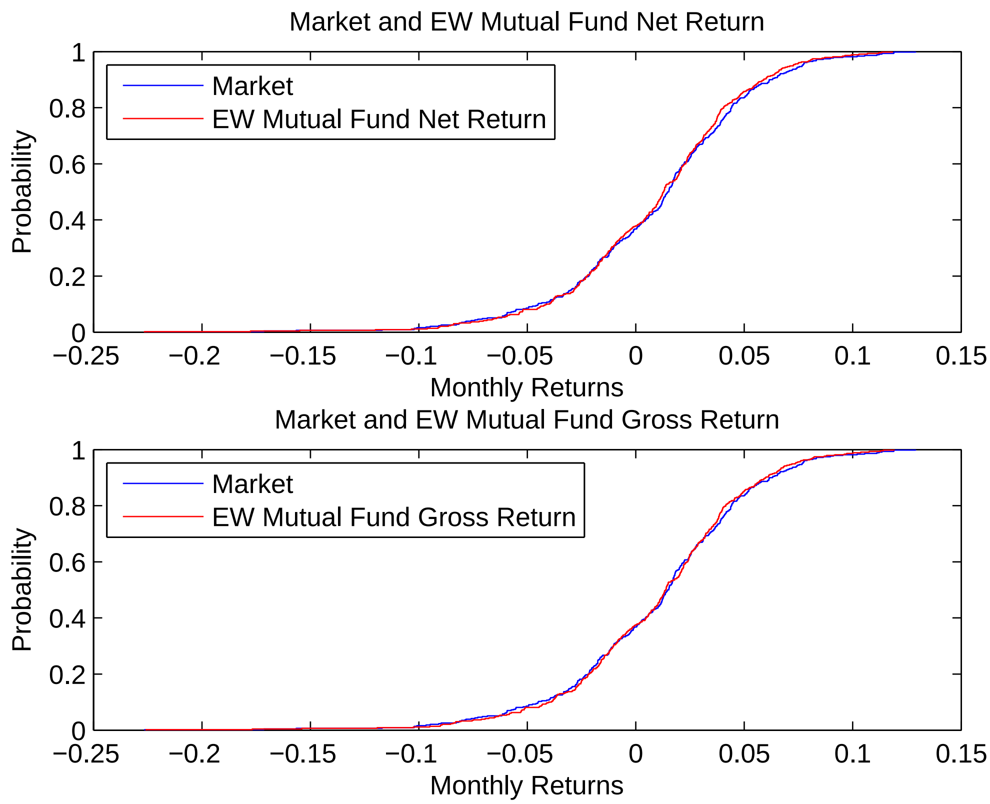

Table 1.4: Stochastic Dominance Test Statistics for EW Mutual Fund and Market Returns

This Table shows the stochastic dominance test results between the market and equally-weighted mutual fund returns. The sample includes all domestic actively managed equity mutual funds in the CRPS-MFLINK merged dataset from March 1980-December 2015. Panel A reports the SD test results for net returns and Panel B reports the test results for gross returns. The P-value is based on subsampling, which takes samples without replacement of various block sizes from the original sample. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

		Test Stat	Subsample Block Size		
			10	30	50
Panel A: Market and EW Mutual Fund Net Returns					
Average Mutual Fund	FSD	0.58	(0.00)	(0.00)	(0.00)
vs. Market	SSD	0.01	(0.00)	(0.00)	(0.02)
	TSD	0.001	(0.01)	(0.01)	(0.02)
Market	FSD	0.27	(0.00)	(0.00)	(0.00)
vs. Average Mutual Fund	SSD	0.01	(0.01)	(0.00)	(0.00)
	TSD	0.001	(0.05)	(0.04)	(0.00)
Panel B: Market and EW Mutual Funds Gross Returns					
Average Mutual Fund	FSD	0.41	(0.00)	(0.00)	(0.00)
vs. Market	SSD	0.01	(0.00)	(0.01)	(0.03)
	TSD	0.001	(0.00)	(0.01)	(0.01)
Market	FSD	0.38	(0.00)	(0.00)	(0.00)
vs. Average Mutual Fund	SSD	0.01	(0.00)	(0.00)	(0.00)
	TSD	0.001	(0.00)	(0.00)	(0.01)

Figure 1.2: CDF of Aggressive and Growth Funds Returns

This Figure plots the CDF of aggressive and growth fund returns. In the first Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of aggressive fund returns. In the second Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of growth fund returns. The sample period is from March 1980 and December 2015.

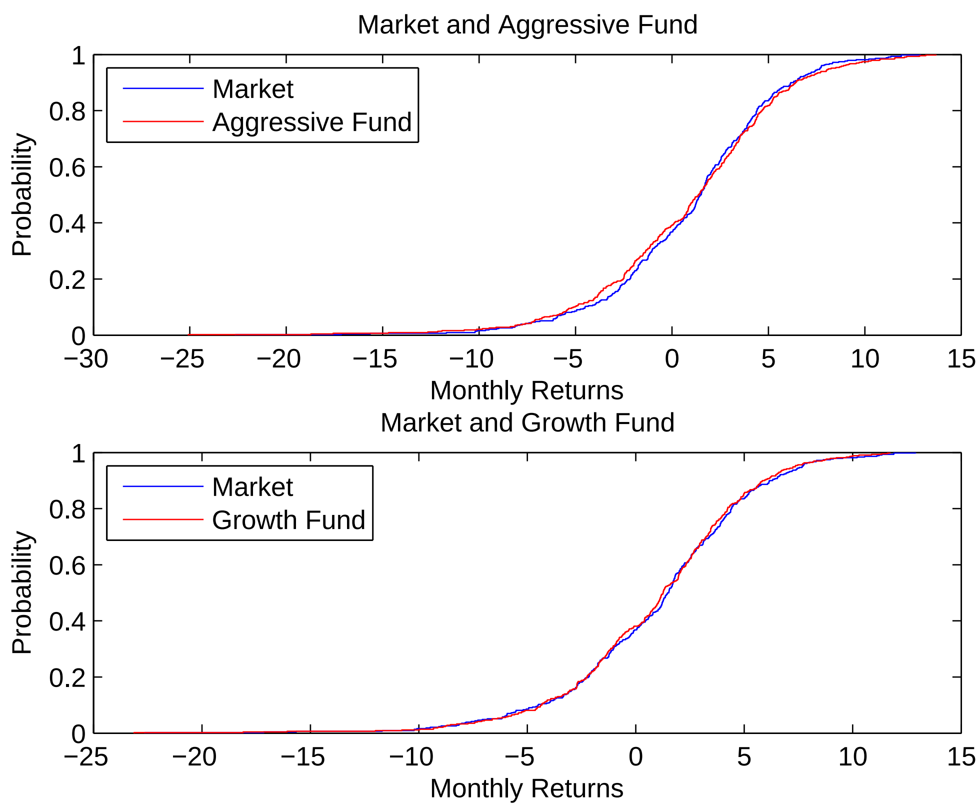

Figure 1.3: CDF of Growth & Income and Income Funds Returns

This Figure plots the CDF of growth & income and income fund returns. In the first Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of growth & income fund returns. In the second Panel, the solid blue line is the CDF of the market returns and the red line is the CDF of income fund returns. The sample period is from March 1980 and December 2015.

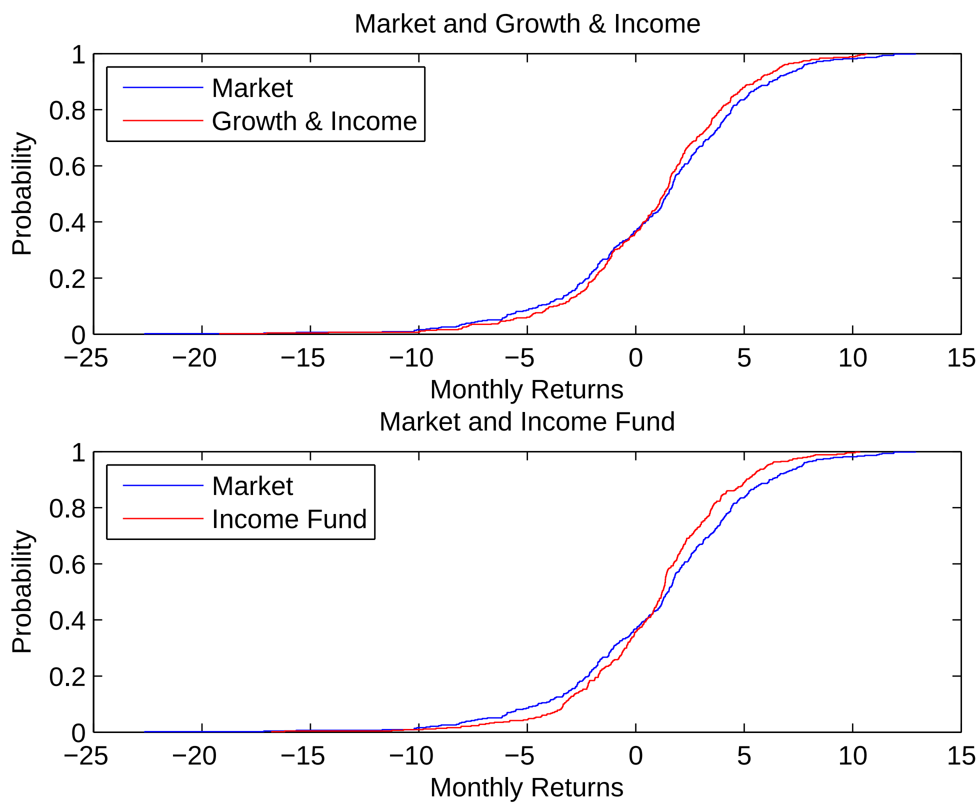

Table 1.5: Stochastic Dominance Test Results for the Market and Four Mutual Fund Classes

This Table reports the stochastic dominance test results for returns of four mutual fund classes and the market. An entry in the table means that the mutual fund style on the left dominates the mutual fund style/market at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

Panel A: EW Net Returns					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	SSD		-		
Income	TSD	TSD	TSD	-	
Growth & Income	TSD	TSD	TSD		-
Panel B: EW Gross Returns					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	TSD		-		
Income	TSD	TSD	TSD	-	
Growth & Income	TSD	TSD	TSD		-

Table 1.6: Fund Returns During Recessions and Expansions

This Table reports the stochastic dominance test results for the returns of four mutual fund classes and the market during NBER recessions and NBER expansions. Our aggregate sample spans 430 months of data from March 1980 until December 2015, among which 55 are NBER recession months (13%). An entry in the table means that the mutual fund style on the left dominates the mutual fund style/market at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

Panel A: EW Net Returns during NBER Expansions					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	SSD		-		
Income	TSD	TSD	TSD	-	
Growth & Income	TSD	TSD	TSD		-

Panel B: EW Net Returns during NBER Recessions					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	TSD	TSD	-		
Income	SSD	SSD	SSD	-	
Growth & Income	SSD	SSD	SSD		-

Table 1.7: Summary Statistics for Monthly Explanatory Returns for Four-factor and Five-factor Models

R_M is the return on a value-weighted market portfolio of NYSE, Amex, and NASDAQ stocks and R_f is the 1-month Treasury bill rate. The construction of SMB_t and HML_t follows Fama and French (1993). The momentum return, MOM_t, is the simple average of the month t returns on the two high momentum portfolios minus the average of the returns on the two low momentum portfolios. The construction of $Liqidity_t$ follows Pástor and Stambaugh (2003). All of the factors are obtained through WRDS. The Table shows the average monthly returns, the standard deviation of monthly returns, and the t-statistic for the average monthly returns. The period is March 1980 through December 2015.

$R_M - R_f$	SMB_t	HML_t	MOM_t	$Liqidity_t$
0.63	0.12	0.26	0.61	0.51
(4.49)	(3.05)	(3.01)	(4.56)	(3.67)

Table 1.8: Performance of Equally-weighted Portfolio of Funds

This Table provides the four-factor model regression result for the entire actively managed equity mutual fund population, as well as for aggressive, growth, growth and income, and income funds. The regression are based on monthly data between March 1980 and December 2015. Each Panel contains the estimated alpha, the estimated exposures to the market, size, value, and momentum factors. Figures below are the coefficient value denote the Newey–West (1987) heteroskedasticity and autocorrelation consistent estimates of p-values under the null hypothesis that the regression parameters are equal to zero.

	$\hat{\alpha}$(annual)	$\hat{\beta_m}$	$\hat{\beta_{smb}}$	$\hat{\beta_{hml}}$	$\hat{\beta_{mon}}$
Aggressive	-0.82%	0.98	0.31	-0.09	0.04
	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)
Growth	-0.73%	0.96	0.10	-0.01	0.01
	(0.12)	(0.00)	(0.00)	(0.15)	(0.09)
Growth & Income	-0.59%	0.91	-0.05	0.14	-0.03
	(0.11)	(0.00)	(0.00)	(0.00)	(0.01)
Income	-0.74%	0.95	-0.09	0.26	-0.03
	(0.03)	(0.00)	(0.00)	(0.01)	(0.02)
All	-0.72%	0.94	0.07	0.03	0.00
	(0.12)	(0.00)	(0.00)	(0.02)	(0.02)

Table 1.9: Four-factor Risk Adjusted Return Performance

This Table reports the stochastic dominance test result for four-factor model risk adjusted returns for the four classes of mutual funds. An entry in the Table means that the mutual fund style on the left dominates the mutual fund style at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance. The sample period is from March 1980 through December 2015.

Panel A: Equal Weighted Risk Adjusted Net Returns Based on Four Factor Models				
	Aggressive	Growth	Income	Growth & Income
Aggressive	-			
Growth	SSD	-		
Income	SSD		-	
Growth & Income	SSD	SSD	SSD	-

Table 1.10: Investment Strategy Based on SD and MV approach

This Table reports the summary statistics of returns for portfolios of second order undominated funds, first order dominated funds, and MV efficient mutual funds between 1995-2015. At the beginning of each year, we form mutual fund portfolios based on the stochastic dominance or the mean-variance efficient test results of the most recent 60 month returns. We hold the portfolio for one year and rebalance annually. S_U denotes second order undominated funds.F_D denotes first order dominated funds. Column 2 shows the average number of mutual funds held in each portfolios. Column 3-6 reports the summary statistics of a portfolio's monthly equal-weighted net return.

	No. of funds	Net return (%/Month)	Std.Dev	Skewness	Kurtosis
S_U	45	1.92%	3.02	0.12	4.81
F_D	1016	0.11%	4.61	-0.97	5.92
MV efficient	67	1.42%	3.21	-0.54	5.64

Table 1.11: Five-factor Risk Adjusted Return

This Table reports the stochastic dominance test result for five-factor model risk adjusted returns for four classes of mutual funds. An entry in the Table means that the mutual fund style on the left dominates the mutual fund style at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

Panel A: Equal Weighted Risk Adjusted Net Return Based on Five Factor Model				
	Aggressive	Growth	Income	Growth & Income
Aggressive	-			
Growth	SSD	-		
Income	SSD		-	
Growth & Income	SSD	SSD	SSD	-

Figure 1.4: CDF for VW Mutual Fund and Market Returns

This Figure plots the CDF of the VW mutual fund and market returns. In the first Panel, the solid blue line is the CDF of market returns and the red line is the CDF of VW mutual fund net returns. In the second Panel, the solid blue line is the CDF of market returns and the red line is the CDF of VW mutual fund gross returns. The sample period is from March 1980 and December 2015.

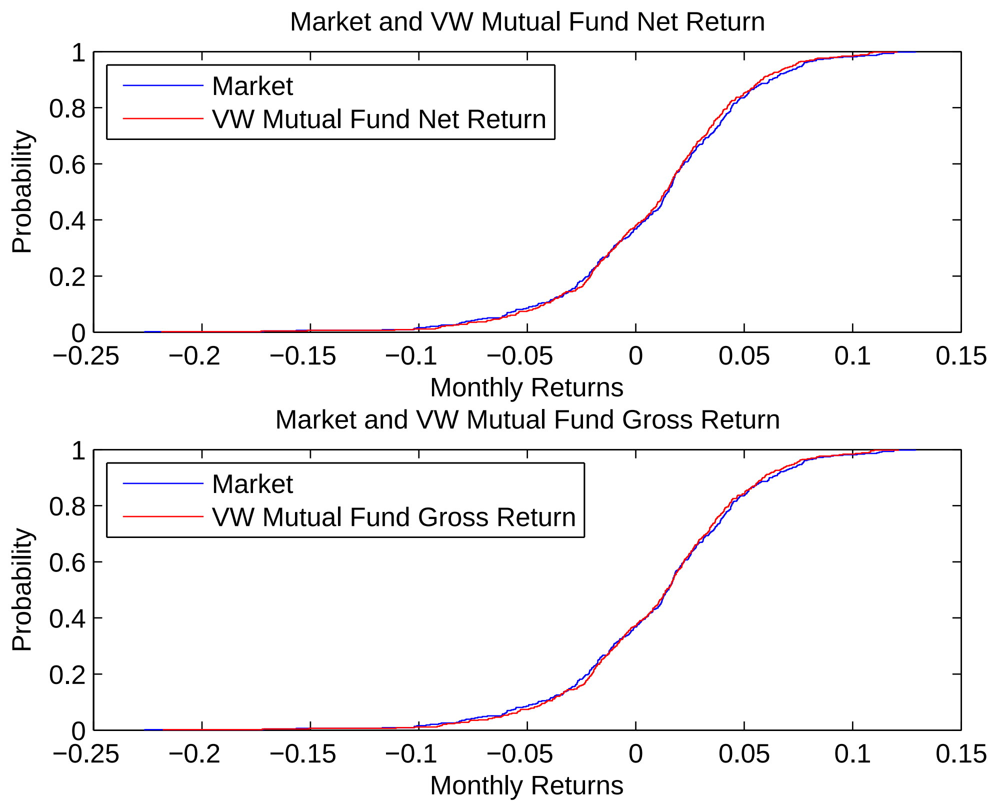

Table 1.12: Stochastic Dominance Test Statistics for VW Mutual Fund and Market Returns

This Table shows the stochastic dominance test results between the market and value-weighted mutual fund returns. The sample includes all domestic actively managed equity mutual funds in the CRPS-MFLINK merged dataset from March 1980-December 2015. Panel A reports the stochastic dominance test results for net returns and Panel B reports the stochastic dominance test results for the gross return. P-values are based on subsampling,which takes samples without replacement of various block sizes from the original sample. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

		Test Stat	Subsample Block Size		
			10	30	50
Panel A: Market v.s.VW Mutual Fund Net Returns					
Average Mutual Fund	FSD	0.44	(0.00)	(0.00)	(0.00)
vs. Market	SSD	0.01	(0.00)	(0.00)	(0.01)
	TSD	0.001	(0.05)	(0.05)	(0.04)
Market	FSD	0.31	(0.00)	(0.00)	(0.00)
vs. Average Mutual Fund	SSD	0.01	(0.00)	(0.00)	(0.00)
	TSD	0.001	(0.00)	(0.01)	(0.00)
Panel B: Market v.s.VW Mutual Fund Gross Returns					
Average Mutual Fund	FSD	0.37	(0.00)	(0.00)	(0.00)
vs. Market	SSD	0.01	(0.00)	(0.06)	(0.04)
	TSD	0.001	(0.02)	(0.05)	(0.05)
Market	FSD	0.34	(0.00)	(0.00)	(0.00)
vs. Average Mutual Fund	SSD	0.02	(0.00)	(0.00)	(0.00)
	TSD	0.001	(0.00)	(0.00)	(0.00)

Table 1.13: Stochastic Dominance Test Result for the Market and Four Mutual Fund Classes

This Table reports the stochastic dominance test results for the returns of the four mutual fund classes and the market. An entry in the table means that the mutual fund style on the left dominates the mutual fund style/market at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

Panel A: VW Net Returns					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	SSD		-		
Income	TSD	TSD	TSD	-	
Growth & Income	TSD	TSD	TSD		-

Panel B: VW Gross Returns					
	Aggressive	Growth	Market	Income	Growth & Income
Aggressive	-				
Growth	TSD	-			
Market	TSD		-		
Income	TSD	TSD	TSD	-	
Growth & Income	TSD	TSD	TSD		-

Table 1.14: Risk Adjusted Return Performance for Value-weighted Mutual Funds

This Table reports the stochastic dominance test results for four-factor model and five-factor model risk adjusted returns for four classes of mutual funds. An entry in the table means that the mutual fund style on the left dominates the mutual fund style at the top. FSD denotes first order, SSD denotes second order, and TSD denotes third order stochastic dominance.

Panel A: Value Weighted Risk Adjusted Net Return Based on Four-factor Model				
	Aggressive	Growth	Income	Growth & Income
Aggressive	-			
Growth	TSD	-		
Income	TSD		-	
Growth & Income	TSD	SSD	SSD	-

Panel B: Value Weighted Risk Adjusted Net Return Based on Five-factor Models				
	Aggressive	Growth	Income	Growth & Income
Aggressive	-			
Growth	TSD	-		
Income	TSD		-	
Growth & Income	TSD	SSD	SSD	-

Part II

What We Learn from China's Rising Shadow Banking: Exploring the Nexus of Monetary Tightening and Banks' Role in Entrusted Lending

(joint with Kaiji Chen and Tao Zha)

Abstract

We argue that China's rising shadow banking was inextricably linked to po- tential balance-sheet risks in the banking system. We substantiate this argument with three didactic ndings: (1) commercial banks in general were prone to engage in channeling risky entrusted loans; (2) shadow banking through entrusted lending masked small banks' expo- sure to balance-sheet risks; and (3) two well-intended regulations and institutional asym- metry between large and small banks combined to give small banks an incentive to exploit regulatory arbitrage by bringing o-balance-sheet risks into the balance sheet. We reveal these ndings by constructing a comprehensive transaction-based loan dataset, providing robust empirical evidence, and developing a theoretical framework to explain the linkages between monetary policy, shadow banking, and traditional banking (the banking system) in China.

Key Words: Regulatory arbitrage, asset pricing, institutional asymmetry, entrusted loans, risk taking, shadow loans, bank loans, nonloan investment, nonbank trustees, small banks, large banks, balance sheet, optimal decisions.

JEL Classification: G28, E02, E5, G11, G12.

Definition of "regulatory arbitrage:" a practice whereby firms capitalize on loopholes in regulatory systems in order to circumvent unfavorable regulation[s]. **Investopedia**

Shadow banking is defined as "*credit intermediation involving entities and activities outside the regular [traditional] banking system or nonbank credit intermediation in short.*" **Financial Stability Board (2013)**.

The size and rapid growth of shadow banking in China warrants particular attention. **Financial Stability Board (2014)**

2.1 Introduction

In the aftermath of the unprecedented stimulus of four trillion RMBs injected by the Chinese government to combat the 2008 financial crisis, the People's Bank of China (PBC) pursued contractionary monetary policy by tightening money supply between 2010 and 2013. The persistent policy of monetary tightening resulted in a simultaneous fall of bank loans and deposits and at the same time a rapid rise of shadow banking (Figures 1 and Figures 2). A principal component of China's shadow banking consists of entrusted loans, a lending activity between nonfinancial firms with commercial banks or nonbank financial companies acting as trustees or middlemen (Figure 3). In particular, the bottom panel of Figure 2 shows that while the total amount of entrusted loans increased during the monetary tightening period of 2010-2013, its share in the sum of entrusted lending and bank lending more than tripled from 6.6% in 2010 to 22% in 2013.

This conspicuous phenomenon has caused concerns of both policymakers and researchers about how the rapid rise of off-balance-sheet entrusted lending would bode ill for China's banking system. By law, commercial banks cannot undertake credit risks associated with entrusted lending.[1] But the law enacted in May 2000 by the

[1] The concept of "entrusted loans" was officially discussed by the PBC's "General Rules on Loans" issued in 1996. A subsequent law, enacted in May 2000, explicitly states that commercial banks as trustees in entrusted loans can only receive commission fees and cannot undertake credit risks.

PBC was too general at that time to be implemented in practice until mid-2014. Prior to 2014 the PBC, in a series of "Financial Stability Reports," expressed concerns of spillover risks to the banking system from shadow lending and pointed to a possibility of *regulatory arbitrage* exploited by banks to take on such risks.[2] The report, however, did not identify which specific regulations gave banks an incentive to exploit regulatory arbitrage. And there has been little academic research that addresses this broad and important issue.

This paper is to fill this vacuum in the literature and study related issues on the linkages between monetary policy, shadow banking, and traditional banking. To identify banking regulatory loopholes and which types of banks that exploited these loopholes and to assess what kind of consequences such an exploitation brought into the banking system, we take as given the macroeconomic trends of monetary aggregates and entrusted loans displayed by Figures 1and 2 and focus on two distinct but related questions: (a) were Chinese banks prone to engage in channeling risky entrusted loans in response to monetary policy changes and (b) if so, how did the risk of shadow loans spill over into the banking system's balance sheet? To frame an answer to these two questions in a coherent way, we provide both empirical and theoretical analyses. The empirical analysis is based on the transaction-based loan data constructed by us and the theoretical framework is grounded in China's unique institutional characteristics.

We complete these analyses with four distinct but related contributions. First, we manually collect and construct a comprehensive transaction-based micro dataset on entrusted loans by merging entrusted-loan announcements (the most important source), nonfinancial firms' annual reports, and banks' annual reports, all downloaded from the WIND database (the data information system created by the Shanghai-

[2]See, for example, page 174 in the PBC's 2013 Financial Stability Report. Similar concerns about regulatory arbitrage were expressed by the Chinese Banking Regulatory Commission in its 9 May 2011 regulation and the State Council in its 10 December 2013 notice.

based company called WIND Co. Ltd., the Chinese version of Bloomberg). We verify our dataset with various Financial Stability Reports published by the PBC. The Bankscope database (a comprehensive, global database of banks' financial statements, ratings, and intelligence, provided by Bureau Van Dijk) is also used for obtaining other balance-sheet information such as capital adequacy ratio. We read through more than a thousand relevant announcements line by line and cross-check the data from different sources to decipher the reporting nuances in the Chinese language, eliminate redundant and duplicated observations, and obtain accurate and comprehensive data for entrusted lending facilitated by banks and nonbank trustees. During this construction process that has taken us several years to complete and is still continuing to refine the dataset, we identify lending firms, borrowing firms, and, most important of all, trustees that facilitated entrusted lending between nonfinancial firms. Our subsequent empirical and theoretical work shows how and why, among different types of trustees, banks behaved differently from nonbank trustees and how and why, among banks, small banks behaved differently from large banks. Our data sample begins in 2007 and ends in 2013 with over 750 unique observations. China's shadow banking began in 2007, accelerated during the period of monetary tightening after the government's 2008-2009 economic stimulus, and was then heavily regulated from mid-2014 forward. Throughout 2014-2015, the Chinese Banking Regulatory Commission (CBRC) first issued and then implemented new regulations specifically prohibiting banks from taking on credit risks through entrusted lending. Thus, the period of 2007-2013 is a critical period for us to understand the issues raised above.

With the constructed micro data, we establish, as a second contribution, empirical evidence of whether banks are prone to engage in risky entrusted lending. The task is challenging because one must identify banks' risk-taking behavior from the data. We address this identification issue by using two instruments. One is to use the transaction-based observations on nonbank trustees to distinguish banks' behavior in our difference-in-difference approach. Since monetary and banking regulations apply to the banking system only, this instrument allows us to isolate the effect of monetary tightening on banks' willingness to facilitate entrusted lending. We show that without this instrument the regressions would underestimate such an effect.

The other instrument relates to different types (qualities) of loans: one type is risky and the other one is not. We use the loan data on the risky type as an instrument. By controlling for the time effect and the industry-fixed effect, we estimate a large number of regressions with double or triple interactions to determine different roles played by banks in channeling entrusted loans to the risky industry. By the risky industry we mean a combination of the real estate industry and 18 overcapacity industries identified by China's Ministry of Industry and Information Technology. We find that during the period of monetary tightening, banks facilitated more entrusted loans than nonbank trustees. Among banks, small banks tended to funnel more entrusted loans to the risky industry than large banks in response to monetary contractions.[3] By contrast, the estimation shows that monetary tightening has an inconsequential effect on nonbank trustees' willingness to facilitating risky entrusted loans.

Third, we provide a detailed discussion of China's unique institutional characteristics that underlay banks' incentives to channel entrusted loans, especially risky ones, during the period of monetary tightening. One unique feature of monetary policy in China is to use monetary aggregates as a major target to stabilize macroeconomic fluctuations. Interest rates were not a major macroeconomic stabilizer until 2014 at the earliest. The main purpose of monetary policy in China has been to control credits and deposits in the banking system. Monetary aggregates such as M2 are a primary

[3] Large banks, controlled and protected by the state, are the Industrial and Commercial Bank of China, the Bank of China, the Construction Bank of China, the Agricultural Bank of China, and the Bank of Communications. The Bank of Communications, initially listed in the Hong Kong Stock Exchange, has officially become the fifth largest state-owned bank since May 16, 2006. The other commercial banks are small relative to these large five banks, including among others China CITIC Bank, China Everbright Bank, China Merchants Bank, Shanghai Pudong Development Bank, the Industrial Bank of China, and the Bank of Beijing.

target to accomplish this task. As is evident in Figure 1, growth in money supply moved in tandem with growth in bank credits and deposits. In addition to monetary policy, there were two unique regulatory restrictions specific to China's banking system: the legal ceiling on the ratio of loans to deposits (LDR) imposed by the PBC on each commercial bank, which we call the "LDR regulation," and the regulation prohibiting commercial banks from expanding bank loans to the risky industry, which we call the "safe-loan regulation."

Monetary tightening gave banks a stronger incentive to circumvent these regulations. As the PBC tightened money supply, bank deposits fell. The pressure built up on deposit shortages, which exposed banks to the risk of violating the LDR regulation.[4] Chinese small banks incurred higher costs, implicit or explicit, than large banks to acquire additional deposits when facing random deposit shortfalls. As a result, the LDR and safe-loan regulations, together with institutional asymmetry between large and small banks in coping with unexpected deposit shortfalls, gave small banks an incentive to take advantage of *regulatory arbitrage*. One effective way for regulatory arbitrage is to increase nonloan investment that was *not* subject to the LDR and safe-loan regulations and at the same time reduce bank loans that were subject to these two regulations. More important is the fact that such nonloan investment is on the asset side of *bank balance sheet*. One principal component of nonloan investment was in the form of the beneficiary rights of entrusted loans funneled by the banks, which we call "entrusted rights" for short. As we show in Section 2.5, nonloan investment was significantly correlated with entrusted lending for small banks, but not for large banks, during the period of a simultaneous fall in monetary aggregates and a rapid rise in entrusted lending (Figure 2). What was supposed to be the risk outside the banking system showed up on small banks' balance sheet. Consequently, shadow banking was used by small banks to mask credit risks in the banking system

[4]For detailed discussions of this regulation risk, see Sections 2.4.2 and 2.4.2 as well as various "Financial Stability Reports" published by the PBC.

by cleverly circumventing the regulatory restrictions.

To place our empirical findings and China's institutional features in a coherent conceptual framework, we develop a theory of banks' optimal portfolio choice subject to China's unique LDR and safe-loan regulations. The theoretical model, constituting a fourth contribution of the paper, is designed to be tractable for obtaining intuitive results. We show that when the deposit withdrawal risk increases as a result of monetary tightening, the small bank will optimally increase investment in risky assets that are not counted as part of bank loans and thus not subject to the LDR and safe-loan regulations. An increase in nonloan risky investment effectively offsets the extra costs of meeting deposit shortfalls faced by the small bank to satisfy the LDR regulation. The small bank, therefore, kills two birds with one stone. The stone is an increase of nonloan risky investment, one bird is the safe-loan regulation, and the other bird is the LDR regulation. Our theoretical predictions are consistent with our empirical findings. A novel feature of our theory is that the small bank exploits regulatory arbitrage by trading off the regulation risk of bank loans with the default risk of shadow loans, a unique Chinese institutional characteristic.

All four elements—micro data, empirical evidence, institutional characteristics, and theory—are woven together as a composite framework for understanding banks' risk-taking incentive that underlay banks' active participation in shadow banking and the resultant financial risk that may have endangered the health of China's banking system. Our empirical and theoretical findings offer one of the didactic lessons: how well-intended banking regulations can generate a perverse incentive for banks to take advantage of regulatory arbitrage. The well-intended regulations were designed to prohibit banks from directly engaging in risky bank loans on the one hand restrict the amount of bank loans by the LDR ceiling on the other hand. Our study demonstrates that these well-intended regulations had an unintended consequence: they encouraged Chinese small banks to bring supposed off-balance-sheet risks into on-balance-sheet risks during the period of monetary tightening *through the means of risky entrusted lending.*

The rest of the paper is organized as follows. Section 2.2 reviews the literature complementary to our paper. Section 2.3 details how our transaction-based data are constructed. Section 2.4 provides robust empirical evidence on banks' risk-taking behavior in channeling entrusted loans. Section 2.5 presents the institutional details relevant to our empirical and theoretical analyses. Section 2.6 develops our theory and offers its implications and predictions. Section 2.7 concludes the paper.

2.2 Literature Review

There are several strands of literature that are relevant to our paper. One strand of literature is theoretical, represented by Bianchi and Bigio (2014) who develop a theoretical framework for evaluating the tradeoff faced by the ex-ante homogeneous bank between profiting from more loans on the one hand incurring the liquidity risk exposure associated with a potential reserve shortfall on the other hand.[5] Our theoretical work builds on Bianchi and Bigio (2014) but with unique Chinese institutional characteristics. In particular, bank loans are subject not to reserve shortfalls but to deposit shortfalls during the period of monetary tightening. The problem facing Chinese banks, especially small banks, is not a reserve requirement, but the LDR ceiling constraint and the safe-loan regulation imposed by the PBC. Another new feature of our theoretical model is that Chinese banks face a tradeoff between the regulation risk associated with bank loans and the default risk associated with shadow loans through risky nonloan investment.

Another strand of literature is empirical, represented by Jiménez et al. (2014) who

[5] In other banking works such as Gertler and Kiyotaki (2010) and Christiano and Ikeda (2013), shocks to the bank equity, coupled with the credit constraint, affect the supply of bank loans, as these shocks exacerbate the incentive problem of banks. Accordingly, the focus of those papers is to explain the effects of policies to recapitalize the banks.

utilize the Spanish loan data to study the effect of monetary policy expansion on the supply of traditional bank loans to risky firms. They introduce triple interactions among monetary policy, bank characteristics, and borrower characteristics into regressions of the credit supply. Our paper, by contrast, studies the bank's risk-taking behavior in facilitating shadow loans during the period of monetary tightening. More important are our results suggesting that the reason for the risk-taking behavior of banks in China is sharply different from that in the developed countries because China's unique institutional background plays a critical role in the close relationships between monetary tightening, bank loans, and shadow loans.

Both our empirical and theoretical findings contribute to the growing literature on China's shadow banking. First, some of our findings are complementary to Hachem and Song (2015). Both our work and their paper highlight China's regulations on banks' LDRs as a key to understanding the rapid growth of China's shadow banking activity. Hachem and Song (2015) focus on the effect of the LDR constraint on the *liabilities of banks' balance sheet*, via banks' issuance of so-called "wealth management products" (WMPs) as an alternative to deposits to circumvent such a regulation. Accordingly, the shadow-banking risk in Hachem and Song (2015) is a maturity mismatch as short-maturity WMPs are used to finance long-term loans. By contrast, our study on entrusted lending and its linkage to risky nonloan assets on banks' balance sheet shed light on the impact of China's rising shadow banking from the viewpoint of *the asset side of banks' balance sheet*. Our empirical findings point to the default risk of such shadow loans that banks may choose to bear as a tradeoff against the regulation risk stemming from both the LDR ceiling and the safe-loan law.

Several recent empirical papers explore the micro-level entrusted loan data from a perspective of firms. For example, He et al. (2015) investigate the reaction of stock prices of both issuing and receiving firms to an entrusted-loan announcement. Allen et al. (2015) explore which types of lending firms tend to make entrusted loans and their motives in making affiliated and unaffiliated entrusted loans. Qian and Li (2013) provide an analysis of entrusted lending as an alternative way of external funding to bank loans when the borrower and the lender have an affiliated relationship. None of these papers, however, study the role of banks in facilitating entrusted loans and the importance of the unique institutional background behind banks' ultimate incentive for partaking in such shadow lending.[6]

Our paper also contributes to the literature on monetary transmission mechanism. Prior to Jiménez et al. (2014), Kashyap and Stein (2000) are the first to use the bank-level data to identify the effect of monetary policy on credit supply via banks' liquidity position. Subsequently, Ivashina and Scharfstein (2010) use the syndicated-loan data to understand the effect of the 2008 financial crisis on the supply of bank credit to corporations with different exposures to drawdown risks of credit lines. Like Ivashina and Scharfstein (2010), monetary tightening also has two effects in our paper: a direct effect on reduction of deposits committed by firms and households and an indirect effect on the rise of deposit withdrawal risk. Various government and financial reports document both effects during the period of monetary tightening in 2010-2013. Unlike Ivashina and Scharfstein (2010), bank loans in China were relatively safe as the government either implicitly guaranteed these loans or explicitly prohibited risk-taking loans through its strict regulations. A more serious problem lay in shadow loans that were not subject to strict regulations until 2014. Our paper takes a first step in identifying and quantifying the effect of monetary policy contractions on banks' roles in risky entrusted lending during the period of monetary contractions between 2010 to 2013.

More generally, our paper identifies the institutional asymmetry between large

[6]Various non-academic policy articles argue that the development of shadow banking in China might bear risks to China's financial system. See, for example, Adrian et al. (2013), Elliott and Yu (2015), the 2011 "Global Research Report" of the HSBC, the 2013 Nomura Global Report on "China: Rising Risks of Financial Crisis," the 2014 "Half-Yearly Monetary and Financial Stability Report" of the Hong Kong Monetary Authority (HKMA), and various PBC reports.

and small banks in costs of acquiring additional deposits in the event of unexpected deposit shortfalls. The institutional asymmetry, together with the LDR and safe-loan regulations, gave a perverse incentive for small banks to exploit regulatory arbitrage by bringing risky shadow loans into the balance sheet under a different asset category that was not subject to the LDR and safe-loan regulations. Furthermore, our paper identifies a mechanism in which small banks brought off-balance-sheet risks into the balance sheet. These analyses shed light on the importance of designing a comprehensive package of regulations that would lead to right incentives for banks to make loans or invest in risky assets.

2.3 Data Construction and Description

The micro loan data used in this paper consist of transactions of entrusted loans between Chinese firms, facilitated by trustees as middlemen. The sample is from 2007 to 2013. We read various data sources line by line and combine them to ensure the accuracy of our manually constructed dataset. In this section, we first describe how we construct our transaction-based dataset and then provide relevant descriptive statistics.

2.3.1 Data Construction

We first collect all the pdf files of raw entrusted-loan announcements made by listed firms in China. Listed firms are those that issue A-share stocks to the public and thus are listed in China's stock exchanges. Chinese law requires listed lending firms to make public announcements about each entrusted-loan transaction. Listed borrowing firms could choose to make announcements but are not required by law. In 2005 China Securities Law Article 67 also requires all listed firms to announce major events which may have influenced their stock prices.[7] In 2011, according to Article 2

[7]The Chinese Securities Regulatory Commission (CSRC) publishes such documents at `http:`

of the CSRC's "Rules for Information Disclosure by Companies Offering Securities to the Public," listed firms have responsibility to disclose all entrusted-loan transactions. Moreover, according to two disclosure memoranda provided by the Shenzhen Stock Exchange in 2011, a listed company must disclose information of entrusted loans as long as its subsidiary firm is a lender of entrusted loans, even if the company itself is not a direct lender.

A raw announcement made for each transaction concerns either a newly originated loan or a repaid loan. Information in each raw announcement contains the names of both lender and borrower, the amount transacted, and relevant financial information if applicable. For each year between 2010 and 2013 , we verify the number of our collected *raw* announcements against the number published by the PBC's 2011-2014 Financial Stability Reports (the reports publish the numbers in the previous years). Figure 2.4 plots the numbers of transactions. One can see from the figure that the discrepancy between our data and the numbers published by the Financial Stability Reports is of little importance. Although both our data source and the PBC's data source are from WIND, at the time when the PBC reported the number of announcements, some companies had not yet made announcements until a later year. Some of these delayed announcements are included in our data collection, which may explain part of this inconsequential discrepancy.

One main reason we must read raw announcements and other relevant documents line by line is that there were often multiple announcements made by an individual lender for the same transaction. In such cases, we manually combine these raw announcements into one announcement. Some announcements were for repayment of entrusted loans. To avoid double counting, we drop those announcements if the same transaction was recorded in previous announcements. Another reason for reading through raw announcements is to obtain the trustee information as much as possible.

`//www.sac.net.cn/flgz/flfg/201501/t20150107_115050.html`.

For some raw announcements, however, the trustee information was missing. In this case we search the annual reports of listed nonfinancial companies that documented the same transactions for the trustee information missing in those announcements. A third reason for reading through raw announcements relates to the nuances of the Chinese language in expressing how the transaction of an entrusted loan was conducted. For some announcements, the amount of a particular entrusted loan was planned but never executed or executed with a different amount in a later announcement. During the loan planning stage, the name of the trustee was often omitted from an announcement. If we had not been careful about these announcements, we would have exaggerated the number and the amount of entrused loans collected. A fourth reason is that we must remove announcements about loans that had already been paid to avoid duplication. The announcements organized this way are the ones we use for the paper and we call them "announcements" rather than "raw announcements" with the understanding that those announcements have been already cleaned up from raw announcements. The total number of raw announcements is 1279. The number of (cleaned-up) announcements is 778.

Our data construction involves extracting the transaction data, manually, from our cleaned-up announcements of new loans. For each announcement, we record the lender and the borrower. Because the same transaction may be announced by both lender and borrower, two announcements may correspond to only one transaction. In such cases we manually compare both announcements to ascertain the accuracy of our processed data set.[8] After the comparison, we merge the two announcements for the same transaction into one unique observation. It turns out that the number of such announcements is only three. Subtracting these three double-counted announcements give us 775 unique observations. The timing of the observation corresponds to the exact timing of the transaction and thus does not necessarily correspond to the time

[8]We find that the lender's announcement typically contains more information than the borrower's.

when an announcement was made. The transaction data constructed from these unique observations are used for our empirical analysis.

The micro transaction-based data of entrusted loans we have collected differ from the aggregate data in several important aspects. First, the aggregate series includes loans between nonfinancial firms as well as four other categories: (i) cash management, (ii) provident funds for housing, (iii) entrusted loans financed by WMPs, and (iv) syndicated loans. In a strict sense, these four other categories are *not* loans entrusted from one nonfinancial firm to another.[9] Indeed, some of these categories, such as cash management and syndicated loans, were re-classified and disqualified as entrusted loans in 2015. According to a 2015 CBRC report, moreover, housing provident funds are not subject to the CBRC regulations on activities of commercial banks that facilitate entrusted loans. Second, announcements are made by listed firms while aggregate entrusted loans may include those transacted between nonlisted firms. Third, aggregate data on entrusted loans may include those repaid already and the same transactions that were reported multiple times. Fourth, it is unclear whether the timing of aggregate entrusted loans corresponds to the time when the loans were reported or the time when actual transactions took place. Despite these differences, however, the aggregate series calculated from our micro data has a similar growth pattern as the macro aggregate data provided by the CEIC (the average growth rate is 40.55% for our micro data and 35.75% for CEIC macro data between 2007 and 2013 and 33.77% for ours and 32.57% for CEIC between 2010 and 2013).

2.3.2 Data Description and Other Data Sources

This section provides key banking characteristics of our constructed transaction data from 2007 to 2013 and describes how our data are merged with other data

[9]Cash management refers to an outsourcing to a bank by a conglomerate to manage short-term funds across its own subsidiaries.

sources.

shows how we arrive at the number of unique observations without duplicated announcements. Thus, the number of unique observations must equal the sum of "NLA" and "NBA" minus "NLABA" (the number of duplications). Clearly, the number of announcements made by lenders was considerably greater than the number of announcements made by borrowers, a fact that is consistent with the legal requirement that listed lending firms must reveal entrusted-loan transactions.

shows a breakdown of transactions by different types of trustees and different types of loans. Affiliated loans involve both lending and borrowing firms within the same conglomerate. While most entrusted loans facilitated by nonbank trustees were affiliated ones, a majority of affiliated loans were channeled by banks, a fact that is not well known. As one can see from the table, no matter whether entrusted loans were affiliated or not, small banks facilitated more transactions than large banks, and large banks faciliated more transactions than nonbank trustees. Thus, banks played a critical role in facilitating both affiliated and non-affiliated entrusted loans.

Small banks accounted for the largest fraction of both loan transactions and loan volume (amount). Table 2.3 shows that the number of entrusted-loan transactions facilitated by small banks took 48% of the total number and the amount of entrusted loans 40% of the total amount. Thus, small banks played a special role in funneling entrusted loans.

2.3.3 Other Data Sources

In addition to the constructed transaction data, our study uses other data sources. One main other source to which our transaction data are bridged is banks' balance-sheet information from WIND, which allows us to compute the correlation of entrusted lending off balance sheet and risky investment on balance sheet as discussed in Section 2.4.2. WIND contains balance-sheet information of listed banks. When an announced transaction identifies the name of the bank, we link the transaction to the WIND information of this bank. For balance-sheet information of nonlisted banks, we resort to Bankscope. If the balance-sheet information of a particular bank is unavailable from WIND or Bankscope, we search the website for this particular bank to obtain its annual reports. There are a total of 19 banks listed in the Hongkong, Shenzhen, or Shanghai Exchange. In 2013, these 19 banks possessed 70% of the total assets of 164 banks and nonbank trustees covered by Bankscope. The five large banks and most joint-stock commercial banks were listed during our sample period. Some local banks or foreign banks are not covered by Bankscope. These missing banks are usually very small and most likely unlisted.[10] Bankscope contains information related to capital adequacy ratio and loan-to-deposit ratio; WIND contains information related to excess reserves and other nonloan asset categories.

Annual reports (in pdf form) of listed nonfinancial companies as well as listed banks are manually collected from the WIND dataset. The WIND dataset also contains some financial information of both banks and nonfinancial firms, which helps expedite the process of data collection and organization as well as verify the accuracy of our constructed dataset.

annual report of a listed nonfinancial company may also contain information about entrusted loans, as used by Allen et al. (2015). The scope of our paper, however, compels us to use information contained in announcements of entrusted loans for several reasons. First, announcements are more likely to disclose names of the banks than annual reports. Of all the transactions in our sample, most facilitating trustees are

[10]In 2015, China had 3 policy banks, 5 state-owned banks, 12 joint-stock banks, 120 local banks, and 75 foreign banks. Policy banks are simply the arms of the PBC for carrying out monetary policy operations and thus are treated as part of the central bank, not commercial banks.

identified by announcements except 52 banks and one nonbank trustee we identify with annual reports. Since our focus is on the role of banks in transacting entrusted loans, the bank information is of vital importance. Second, for a particular transaction, annual reports may contain information about the amount of outstanding entrusted loans, instead of the amount of newly originated loans. For example, in a 2010 announcement of "Shandong Chenming Paper Holdings Limited," the total amount of entrusted loans worth 500 million RMB was recorded; after this loan transaction, there were no additional entrusted loans made in 2010 and 2011 by this company and thus there were no more announcements from the company during this period. In both 2010 and 2011 annual reports of the same company, it listed entrusted loans to its subsidiary "Jiangxi Chenming Paper Holdings Limited" with the total amount of 500 million RMB, because the outstanding loans had maturity dates beyond 2011. Without the knowledge of maturity dates, one would have double counted the number of actual transactions as well as the total amount of newly issued loans.

2.4 Empirical Findings

In this section we undertake the task of establishing evidence of the risk-taking behavior of Chinese banks in channeling entrusted loans during the period of monetary contractions. With our constructed micro dataset, we use two instruments to identify such a risk-taking behavior. One instrument is the data on entrusted lending facilitated by nonbank trustees in our difference-in-difference approach. The other instrument is the data on entrusted lending to the risky industry. The risky industry is identified according to Number 111 of the "2010 Manufacturing Industry Announcement" issued by the Ministry of Industry and Information Technology. The industry includes real estate, iron, steel, coke, ferroalloy, calcium carbide, aluminum, copper smelting, lead smelting, zinc smelting, cement, glass, paper, alcohol, monosodium glutamate, citric acid, tanning, dyeing, and chemical fiber—a total of 19 industries.

We accomplish the task by answering the following questions sequentially. (1) Relative to nonbank trustees, did banks play an important role in entrusted lending during the period of monetary tightening? (2) What type of banks, small or large, was more likely to be engaged in facilitating entrusted loans? and (3) What type of loans, risky or non-risky, did such banks tend to facilitate? Prior to answering these questions, we first document the relationships among risky entrusted loans, their maturities, and their interest rates. These relationships are essential to one of the assumptions in our theoretic model developed in Section 2.4.2.

2.4.1 Maturities and Lending Rates of Entrusted Loans

Each loan transaction is uniquely determined by a quadruple index $s = (t, i, b, j)$, where t represents the year in which the transaction takes place, i the loan recipient (borrower or borrowing firm), b the bank or nonbank trustee that facilitates the loan, and j the loan originator (lender or lending firm). The loan amount is thus denoted by$\mathscr{S}_s$.[11] Since the risky characteristic concerns borrowers only, the characteristics related to j (lending firms) are not the subject of this paper and thus left to the residuals of our various regressions. As a first step, we run the following regression:

$$\mathfrak{s}_s = \alpha + \alpha_t + \alpha_m \mathfrak{m}_s + \alpha_r \mathscr{I}\left(\text{Risky}_i\right) + \varepsilon_s, \tag{2.1}$$

where $\mathfrak{s}_s$ is the interest rate spread between the loan rate and the 7-day CHIBOR rate (measuring the degree of riskiness of each loan), $\mathfrak{m}$ is the loan maturity, α_t controls for the time fixed effect, and $\mathscr{I}\left(\text{Risky}_i\right)$ returns 1 if the borrower is in the

[11]For our transaction-based data, it is not uncommon that a borrower utilizes an entrusted loan only once for the whole sample or that a borrower utilizes two or more entrusted loans in a distant interval of many years.

risky industry and 0 otherwise. The control variable vector α_t includes g_{t-1} (annual change in M2 from the end of $t-2$ and the end of $t-1$), GDP_{t-1}, (annual change in GDP from the end of $t-2$ and the end of $t-1$), and Inf_{t-1} (annual change in the general price level from the end of $t-2$ and the end of $t-1$). The GDP measure is real GDP measured by value added. The inflation series is the GDP deflator; we have experimented with other inflation series as in Nakamura et al. (2014) and Chang et al. (2016) but with almost identical results for all our empirical findings.

After controlling for loan maturities ($\alpha_m \mathfrak{m}_s$), the coefficient α_r reflects the interest rate spread between risky and non-risky lending rates.[12] According to the estimates reported in Table 2.4, additional one-year maturity reduces the lending rate spread over the 7-day CHIBOR rate by 46 basis points. *After we control for maturities*, the spread between risky and non-risky lending rates is 1.28% annually. The significantly estimated coefficient, α_m, indicates that the longer the maturity is, the less risky entrusted lending is. This is a unique feature of Chinese entrusted loans that underlies our theoretical model's assumption that risky assets have a shorter duration than safe loans.

2.4.2 Role of Banks in Entrusted Lending

In this section we answer the question of whether banks played an important role in overall entrusted lending during the period of monetary tightening. To determine such a role of banks, we use the data of entrusted loans facilitated by nonbank trustees as an instrument. This instrument is necessary for us to identify banks' behavior in entrusted loans conditional on changes in monetary policy. The following regression

[12]Except for the characteristic of whether the lending to the borrowing firm is risky, there is no need to control for borrowers' other characteristics because they do not affect the spread. As the interest rate spread, labeled by $\mathfrak{s}$, captures the degree of riskiness as well as the term premium, what should be controlled for are the maturity and other time fixed effects captured by α_t.

involves double interactions between monetary policy and the type of trustees:

$$\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_g g_{t-1} + \beta_b g_{t-1} \mathscr{I}\left(\text{Bank}_b\right) + \text{Control}_b + \varepsilon_s \tag{2.2}$$

where $\mathscr{I}\left(\text{Bank}_b\right)$ controls for the type of trustees and α_t, as defined in Section , is a vector of variables controlling for aggregate time fixed effects other than the effect of monetary policy and captures, for example, business-cycle effects. The variable $\mathscr{I}\left(\text{Bank}_b\right)$ returns 1 if the trustee is a bank and 0 otherwise.[13] The additional control variable Control_b is $\mathscr{I}\left(\text{Bank}_b\right)$.

Following Kashyap and Stein (2000), we use the double-interaction term to capture bank's willingness to be engaged in entrusted lending.[14] Table 2.5 reports the ordinary least squares results of regression (2.2) for all the coefficients (except those of control variables). The coefficient β_b of the double-interaction term $g_{t-1}\mathscr{I}\left(\text{Bank}_b\right)$ captures how much of entrusted lending is facilitated by banks *in addition to* the lending channeled by nonbank trustees when M2 growth changes. From the table one can see that this marginal effect is estimated to be negative and the estimate is highly significant. The negative sign means that monetary tightening (a fall in M2 growth) increases, not decreases, entrusted lending.

The coefficient α_g captures the impact of monetary tightening on entrusted loans *facilitated by nonbank trustees.* The positive value indicates that the amount of entrusted lending facilitated nonbank trustees decreases in response to a fall in M2 growth, reflecting the impact of monetary contractions on the overall economy. Although this term is statistically insignificant, it is necessary for our difference-in-difference approach to controlling for the effect of nonbank trustees in order to capture

[13]Since we do not quantify, at this point, any effect of borrowers on entrusted loans, there is no need to control for borrowers' characteristics, which are simply captured by ε_s. In Sections 2.4.2 and 2.4.2 we expand our analysis by explicitly controlling for borrowers' characteristics.

[14]Kashyap and Stein (2000) do not use the bank dummy as we do, but instead use the balance-sheet information to identify factors that affect banks' willingness to supply loans.

the effect of banks. According to the estimates in Table 2.5, the estimated impact of a one-percentage-point decline in M2 growth *increases* the amount of entrusted lending channeled by banks by 4.20% and this estimate is highly significant. This sharply estimated result indicates that banks played a different role from nonbank trustees in channeling entrusted loans in 2007-2013.

2.4.3 Types of Banks

Given the estimated differences between banks and nonbank trustees in channeling entrusted loans in the face of monetary policy changes, we expand the difference-in-difference regression by taking into account different roles played by different types of banks as

$$\begin{aligned}\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_s \mathscr{I}\left(\mathrm{Small}_b\right) + \alpha_\ell \mathscr{I}\left(\mathrm{Large}_b\right) + \alpha_g g_{t-1} \\ + \beta_s g_{t-1} \mathscr{I}\left(\mathrm{Small}_b\right) + \beta_\ell g_{t-1} \mathscr{I}\left(\mathrm{Large}_b\right) + \mathrm{Control}_b + \varepsilon_s, \quad (2.3)\end{aligned}$$

where $\mathscr{I}\left(\mathrm{Small}_b\right)$ returns 1 if the trustee is a small bank and 0 otherwise; $\mathscr{I}\left(\mathrm{Large}_b\right)$ returns 1 if the trustee is a large bank and 0 otherwise. Other control variables, denoted by $\mathrm{Control}_b$, are listed in Table 2.9.

Table 2.6 reports the estimated results, which are consistent with the previous results. The estimate of α_g is similar to that in Table 2.5. As expected, the estimated coefficients for the two double-interaction terms

$$g_{t-1} \mathscr{I}\left(\mathrm{Large}_b\right) \text{ and } g_{t-1} \mathscr{I}\left(\mathrm{Small}_b\right)$$

sandwich the estimated double-interaction coefficient reported in Table 2.5 for all banks ($-4.63 > -6.05 > -7.15$). The statistical significance of the estimate for all banks in Table 2.5 comes from small banks as reported in Table 2.6. Similarly, the significant impact of monetary changes on entrusted lending via all banks stems from small banks as well. According to Table 2.6, a one-percentage-point fall in M2 growth has a much stronger effect on entrusted loans via small banks than those via large banks in both magnitude and significance: entrusted lending via small banks increases by 5.23% with a less than 1% significance level while entrusted lending via large banks increases by only 2.71%, which is statistically insignificant. M2 growth also has an insignificant impact on entrusted lending facilitated by nonbank trustees. When monetary policy contracts, therefore, small banks' behavior differs quantitatively from nonbank trustees as well as large banks. This evidence is consistent with evidence of why large banks differ from small banks on their balance-sheet behavior as provided in Section 2.4.2.

2.4.4 Types of Loans

In the preceding analysis we use the data on nonbank trustees as an instrument to effectively identify banks' willingness to facilitate entrusted loans. In this section we use the data on entrusted lending to the risky industry as another instrument to identify banks' risk-taking behavior, which involve triple interactions in the following regression.

$$\begin{aligned}\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_{sec} + \alpha_g g_{t-1} + \beta_b g_{t-1} \mathscr{I}\left(\text{Bank}_b\right) + \gamma_n g_{t-1} \mathscr{I}\left(\text{Risky}_i\right) \\ + \gamma_b g_{t-1} \mathscr{I}\left(\text{Bank}_b\right) \mathscr{I}\left(\text{Risky}_i\right) + \text{Control}_{ib} + \varepsilon_s, \quad (2.4)\end{aligned}$$

where $\mathscr{I}\left(\text{Risky}_i\right)$ returns 1 if the borrower is in the risky industry and 0 otherwise, α_{sec} controls for borrowers' characteristics at the industry level, and additional control variables, denoted by Control_{ib}, are listed in Table 2.9. Because the risky character is identified at the industry level according to the 2010 announcement issued by the Ministry of Industry and Information Technology, we need to control for other borrower characteristics at the industry level such as the size, market power (monopoly), capital intensity (labor share), and share of state-owned enterprises (SOEs) in each industry. The control variable α_{sec} has 46 dummies representing 46 classified industries.

Why do we use the industry risk represented by $\mathscr{I}(\text{Risky}_i)$, not firm-specific risks, as an instrument to identify the riskiness of entrusted lending? Firm-specific risks can be diversified by banks, but the industry-level risk is non-diversifiable and it is this kind of risk that Chinese policymakers care about and view as a serious threat to the banking system. A series of laws and regulations aim at curtailing the industry-level risk, which is specifically defined by the law.

With the data on risky entrusted lending as an instrument, the triple-interaction term plays a crucial role in isolating the effect of banks' penchant for channeling risky loans when monetary policy changes. If the triple-interaction term

$$g_{t-1}\mathscr{I}(\text{Bank}_b)\,\mathscr{I}(\text{Risky}_i)$$

were left out of regression (2.4), the double-interaction term $g_{t-1}\mathscr{I}(\text{Risky}_i)$ would capture the effect of monetary policy changes on risky entrusted borrowing no matter who is the trustee. After this double-interaction term is controlled for, the above triple-interaction term helps isolate the effect of monetary tightening on banks' willingness to channel *risky* entrusted lending.[15] Table 2.7 reports the results consistent with the findings reported in Tables 2.5 and 2.6.

The estimate of α_g indicates that a one-percentage-point fall in M2 growth in-

[15]See a similar methodology of Jiménez et al. (2014) in identifying banks' risk-taking behavior.

creases non-risky entrusted lending by nonbank trustees by 5.52% with only the 10% significance level. With the presence of triple interactions, the sum of α_g and the double-interaction term $g_{t-1}\mathscr{I}\,(\text{Risky}_i)$ measures the impact of monetary policy changes on risky entrusted lending channeled by nonbank trustees, which is estimated to be insignificant. By contrast, the impact of monetary policy changes on risky entrusted lending channeled by banks is estimated to be very strong in both magnitude and significance; the estimate indicates that a one-percentage-point decline in M2 growth leads to a 6.58% increase of risky entrusted lending with a less than 1% significance level. The instrument of the data on risky entrusted loans helps identify the difference between banks and nonbank trustees in facilitating risky entrusted loans and determine the magnitude and significance of risky loans channeled by banks in response to monetary contractions.

2.4.5 Types of Loans Interacting with Types of Banks

Since the share of the amount of risky entrusted lending facilitated by nonbank trustees in total risky entrusted loans was only 23.3% during our sample period of 2007-2013, it is not surprising that the impact of monetary policy changes on these loans is estimated to be insignificant. The remaining share was channeled by commercial banks; among them, small banks funneled risky entrusted lending as much as large banks did (37.2% vs. 39.5%). Now that Section 2.4.2 establishes evidence that banks were principally responsible for channeling more *risky* entrusted loans when money growth slowed, a natural question is whether small banks behave differently from large banks as we find in Section 2.4.2. To answer this question, we expand the triple-interaction regression (2.4) by separating large and small banks as follows:

$$\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_{sec} + \alpha_g g_{t-1} + \beta_s g_{t-1} \mathscr{I}\left(\text{Small}_b\right) + \beta_\ell g_{t-1} \mathscr{I}\left(\text{Large}_b\right)$$
$$+ \gamma_n g_{t-1} \mathscr{I}\left(\text{Risky}_i\right) + \gamma_s g_{t-1} \mathscr{I}\left(\text{Small}_b\right) \mathscr{I}\left(\text{Risky}_i\right) + \gamma_\ell g_{t-1} \mathscr{I}\left(\text{Large}_b\right) \mathscr{I}\left(\text{Risky}_i\right)$$
$$+ \text{Control}_{ib} + \varepsilon_s, \quad (2.5)$$

where additional control variables Control_{ib} are listed in Table 2.9. Regression (2.5) allows the interactions between types of loans and types of banks and is thus our benchmark regression for this paper.

The estimated results for nonbank trustees, as reported in Table 2.8, remain the same. That is, nonbank trustees tend to facilitate non-risky, rather than risky, entrusted lending during the period of monetary slowdown. Although risky entrusted lending channeled by both large and small banks increases in response to monetary contractions, small banks tend to do more than large banks in both magnitude and significance. According to the estimates reported in Table 2.8, a one-percentage-point drop in M2 growth has the impact of a 7.57% increase in risky entrusted lending funneled by small banks and the significance level of the estimate is 0.002%, while risky entrusted lending channeled by large banks is estimated to increase by 5.28% increase with the 3% significance level. The significantly estimated impact for banks as a whole, reported in Table 2.7, is between these two estimates ($-5.28 > -6.58 > -7.57$). Consistent with the results reported in Table 2.6, the effect on risky lending via small banks is stronger than that via large banks in both magnitude and significance.

2.4.6 Further Robustness Analysis

In the preceding sections we show that the data on entrusted lending facilitated by nonbank trustees serve as a powerful instrument to help identify banks' behavior. It is therefore necessary to provide a careful analysis of the quantitative importance of this instrument. A nonbank trustee is an ideal trustee as it is the kind of trustee as intended by the law (i.e., the PBC's 2000 guidelines on entrusted lending). Nonbank trustees face no deposit withdrawal risks and bear no credit risks as commercial banks do. Consequently, the banking regulations we have discussed thus far do not apply to these trustees. In this sense nonbank trustees act truly as middlemen. Entrusted loans facilitated by nonbank trustees capture demand from borrowers and supply from lenders. Controlling for these data with the difference-in-difference approach, therefore, enables us to identify banks' willingness to engage in entrusted lending.

A natural question is what the estimated results would indicate if we exclude from the sample the transactions facilitated by nonbank trustees. With this exclusion, the effective sample size is reduced to 650 and the triple-interaction regression represented by (2.4) is reduced to the following double-interaction regression:

$$\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_{sec} + \alpha_g g_{t-1} + \gamma_r g_{t-1} \mathscr{I}\left(\text{Risky}_i\right) + \text{Control}_i + \varepsilon_s, \tag{2.6}$$

where an additional control variable Control_i is listed in Table 2.9. The estimated results are reported in Table 2.10.

As one can see from Table 2.10, all the estimates of the impact of monetary policy changes on entrusted loans channeled by banks, risky or not, have a small magnitude and are statistically insignificant. The absence of the nonbank-trustee instrument creates uninformative results. Without the nonbank-trustee instrument, one may still use the loans channeled by large banks as an instrument to identify small banks' risk-taking behavior as in the following regression similar to the triple-interaction benchmark regression (2.5) but without the data on entrusted loans facilitated by nonbank trustees:

$$\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_{sec} + \alpha_g g_{t-1} + \beta_s g_{t-1} \mathscr{I}\left(\text{Small}_b\right) + \gamma_\ell g_{t-1} \mathscr{I}\left(\text{Risky}_i\right) + \gamma_s g_{t-1} \mathscr{I}\left(\text{Small}_b\right) \mathscr{I}\left(\text{Risky}_i\right) + \text{Control}_{ib} + \varepsilon_s, \quad (2.7)$$

where additional control variables Control_{ib} are listed in Table 2.9. The estimated results are reported in Table 2.7.

One can see from Table 2.7 that the large-bank instrument helps identify the risk-taking behavior of small banks. Indeed, the impact of monetary policy changes on risky entrusted loans funneled by small banks is estimated to be -4.74% with the 5% significance level. But both magnitude and significance are considerably underestimated when compared to the results in Table 2.8. Moreover, since the lack of the nonbank-trustee instrument makes it difficult, if not impossible, to identify large banks' behavior, the estimate of the impact of monetary policy changes on risky entrusted loans channeled by large banks has a minute value (-0.23) without any statistical significance. These analyses demonstrate the practical and quantitative importance of using the data of entrusted loans facilitated by nonbank trustees as an instrument to identify the behavior of banks, large or small.

One of the most important transmission features of China's monetary policy is the unequivocal effect of M2 supply on bank loans and thus on bank deposits. As shown in Figure 2.1, M2 growth and deposit growth move in tandem. By changing monetary policy through control of M2 growth, the government effectively controlled growth of the banking system at least prior to 2014. Indeed, the correlation between M2 and deposit growth rates is as high as 0.93 during the period of 2007-2013 and 0.96 during the period of 2010-2013. When deposit growth slows down, banks' activities on balance sheet, such as growth in traditional bank loans, would slow down accordingly. Banks would have an incentive to engage in off-balance-sheet activities. To see whether our results hold for bank deposits in place of M2, we run the following triple-interaction regression equivalent to the benchmark regression (2.5) except that M2 growth is now replaced by deposit growth:

$$\log \mathscr{S}_s = \alpha + \alpha_t + \alpha_{sec} + \alpha_d d_{t-1} + \beta_s d_{t-1} \mathscr{I}(\text{Small}_b) + \beta_\ell d_{t-1} \mathscr{I}(\text{Large}_b)$$
$$+ \gamma_n d_{t-1} \mathscr{I}(\text{Risky}_i) + \gamma_s d_{t-1} \mathscr{I}(\text{Small}_b) \mathscr{I}(\text{Risky}_i) + \gamma_\ell d_{t-1} \mathscr{I}(\text{Large}_b) \mathscr{I}(\text{Risky}_i)$$
$$+ \text{Control}_{ib} + \varepsilon_s, \quad (2.8)$$

where d_{t-1} represents the growth rate of deposits at $t-1$ (annual change from the end of $t-2$ to the end of $t-1$) and additional control variables, denoted by Control_{ib}, are listed in Table 2.9.

The estimated results in Table 2.12 are very similar to those in Table 2.8. These robust findings, reflecting the close relationship between M2 growth and deposit growth in China, continue to show the difference between large and small banks in channeling risky entrusted loans. Such a behavioral difference, as discussed in Section 2.4.2, is not due to the size difference between large and small banks in their assets or equities, but stems from institutional asymmetry in several important aspects. First, large banks enjoy implicit government guarantees on their bank loans. Second, large banks, being state-owned, are a primary funding source for non-financial SOEs and other large firms of strategic importance to the government. Third, as a result, large banks have a stable and broad customer relationship with both households and firms so that they encounter little difficulty in acquiring additional deposits to weather unexpected deposit shortfalls. These advantages are hardly enjoyed by small banks. Such institutional asymmetry gives small banks, not large banks, a strong incentive to bring their risk-taking behavior off balance sheet as found in this section into their balance-sheet activity. In Section 2.4.2 we provide the relevant institutional background as well as further evidence that small banks were prone to bring the risk off balance sheet into the balance sheet in the form of nonloan investment while there is no such evidence for large banks. In Section 2.4.2 we build a theory for a coherent explanation of such risk-taking behavior of small banks in the context of China's unique institutional background.

2.5 Institutional Asymmetry

In this section we provide a narrative of China's institutional background and discuss the unique features of China's banking system that are pertinent to our paper.

2.5.1 The Usual Suspects

Obvious candidates for explaining the difference in risk-taking behavior between large and small banks relate to balance sheet information that reveals how banks respond to monetary and regulatory policies. The monetary and regulatory authorities in China had in place three major regulations on all commercial banks during 2007-2013: capital requirement, reserve requirement, and LDR requirement. We provide evidence on whether there was a notable difference between large and small banks in meeting each of the three requirements.

First, both large and small banks met the capital requirement by a comfortable margin as shown in Table 2.13. One can see from the table that the difference in capital adequacy ratios between large and small banks was inconsequential and that both their capital ratios were far above the capital requirement ratio of 8%.

Second, small banks had a considerably higher *excess* reserve ratio than large banks. The numbers reported in Table 2.13 are not available in any electronic data format. We read the annual report of each commercial bank in a pdf file downloaded from WIND (each pdf file has over-100 pages) and find the numbers for excess reserves and total deposits in the chapter called "Notes of Financial Statement." We compute the excess reserve ratio for each bank in every year, take a weighted average of these ratios for all the banks within the group (the large or small type) in each year, and then average these ratios across years. As clearly shown in Table 2.13, small banks, like large banks, had no problem managing their reserves and the reported excess reserve ratios indicate that small banks had more cushion than large banks in meeting the reserve requirement.

Third, both large and small banks met the LDR requirement of 75% and the difference in LDR between large and small banks became smaller over time.[16] For the period of monetary tightening (2010-2013), the difference almost did not exist. The issue for banks is not the LDR ceiling per se, but rather the risk of hitting the ceiling due to unexpected deposit shortfalls. Such a risk is an important ingredient in our theory developed in Section 2.4.2.

In summary, all banks large or small met the three major policy requirements and in this respect there is no difference between large and small banks. It is therefore not these policies per se that helped explain the robust empirical findings of how small banks behaved differently from large banks in channeling entrusted loans. The aforementioned obvious balance-sheet candidates are unlikely to be a major explanation of asymmetric responses of small and large banks to monetary policy changes in their risk-taking behavior. A less obvious candidate for explanation is *banks' ability to cope with the pressures of deposit shortfalls*, which has been an intensive topic within the

[16] Since only the PBC (not central banks in many other countries) requires a bank to report the LDR and since Bankscope collects variables that are common across countries, a direct measure of the LDR is not provided by Bankscope. We construct this measure as the ratio of "gross loans" to "total customer deposits." For a listed bank, we verify this measure with the reported LDR published by the bank's annual report and they match. The published ratio must comply with the PBC's requirement by law.

Chinese policy circle. This is a unique feature of China's banking system and has yet to be thoroughly analyzed by researchers. As discussed in the following sections, it is this institutional detail that helps explain the difference in risk-taking behavior between large and small banks.

2.5.2 Banking Regulations against the Macroeconomic Background

Bank loans in China are a major source of financing to fund economic activities; changes in bank loans are largely influenced by monetary policy. As shown in Figure 2.1, the growth rates of M2 and total bank loans moved in tandem, reflecting the unique characteristic of China's monetary policy of controlling bank lending by adjusting growth of monetary aggregates.

In response to the 2008 global financial crisis, the Chinese government injected money supply into the banking system in late 2008 and early 2009 in which growth of M2 doubled and so did growth in bank loans. For fears of rising inflation, the PBC began to tighten money supply and bank lending toward the end of 2009. As a result of monetary tightening, growth in bank loans and deposits fell steadily since 2009. To counter the rapid slowdown in bank loans, shadow banking activities sprang up (Figure 2.2). Entrusted lending in particular has become the second largest financing source of loans after traditional bank lending. The volume of newly originated entrusted loans reached its climax in 2013. In that year, total shadow lending was equivalent to nearly 34% of total social financing excluding stocks and bonds, and the amount of entrusted lending accounted for nearly 49% of total shadow lending.[17]

Both monetary tightening and a series of regulatory changes contributed to the rapid rise of China's shadow banking and to the observed opposite movements in

[17]Total shadow lending is the sum of entrusted loans, trusted loans, and bank acceptances.

bank loans and entrusted loans. Loans between nonfinancial firms, which define the concept of entrusted lending, were practiced in China at the outset of advanced economic reforms in the early 1990s but did not really blossom until after 2009. In 1996 the PBC issued "General Rules for Loans" that allowed entrusted lending. In 2000 the PBC provided formal operational guidelines for commercial banks to be trustees of entrusted loans in its May (No. 100) "Notice on Issues Related to Practices of Commercial Banks in Entrusted Lending." The key requirement in these guidelines was the mandatory participation of a financial institution acting as a trustee to facilitate a loan transaction between two nonfinancial firms. This regulation required the participating financial institution to verify that all the paperwork met various legal forms and requirements. The purpose of this regulation was to encourage financial institutions to use their specialty in monitoring and screening technology to help curtail nonperforming or risky loans.

As found by our empirical analysis in Section 2.4, although entrusted loans facilitated by nonbank trustees tended to be safe, those channeled by banks ended up in the real estate and overcapacity industries. The incentive for banks to engage in funneling risky loans stemmed from a series of regulatory changes and restrictions imposed on banks. In 2006 the State Council, concerned with China's real-estate and overcapacity industry, issued a notice to accelerate the restructuring process of the risky industry. The CBRC took concrete steps in 2010 to curtail expansion of traditional credits from the banking sector to the risky industry. Subsequently, in 2013 the State Council issued an order that strictly prohibited banks from providing new credits to the risky industry.

On top of these regulations, the PBC imposed an additional restriction on traditional loans made by banks. In as early as 1994 the PBC established a 75% ceiling on the ratio of traditional loans to total bank deposits for the entire banking system for the purpose of curbing risk-taking behavior and reducing the potential systemic risk. This ceiling was not credibly enforced until the late 2000s. In 2011, through the CARPAL system (the Chinese version of Basel III), the PBC began to monitor the LDR during the course of the year (quarterly) rather than at the end of the year.

2.5.3 The Last-Minute Rush for Deposits by Small Banks

As M2 growth began to slow down in late 2009, the pressure of unexpected deposit shortfalls against the LDR ceiling began to build up, that is, banks were more vulnerable to deposit withdrawal risks.[18] While the LDR regulation applied to all banks, small banks had disadvantages in attracting additional deposits to meet shortfalls, especially around the time when the LDR was closely monitored by the PBC at the end of the quarter. In fact, the government uses the phrase "the last-minute rush (*chong-shidian* in Chinese)" to refer to the last-minute actions taken by banks to pay high prices to *artificially increase temporary deposits* in order to recoup deposit shortfalls when the monitoring time is near.[19]

In practice, the last-minute rush was more relevant to small banks than large banks. State-owned large banks, with branches in almost every corner of the country and with implicit guarantees from the central government, had advantages of attracting household deposits on a broad basis at low costs. Moreover, because nonfinancial SOEs as well as nonfinancial large non-SOE firms had easy and preferential access to loans made by the large banks (Chang et al., 2016), these firms in return were willing to place additional deposits in large banks when requested by these banks. The large banks' long-standing customer relationships with a broad base of firms and

[18]For detailed discussions of such risks, see the PBC's various "Financial Stability Reports" published in the early 2010s.

[19]See the proclamation "Number 236 Notice on Strengthening Commercial Banks' Deposit Stability Management" jointly announced on 12 September 2014 by the CBRC, the Ministry of Finance, and the PBC.

households enabled them to weather deposit shortages without much cost.

These advantages were hardly enjoyed by small banks, which often had relationships with only local and small firms and whose customer base for deposits was not nearly as broad and stable. As a result, when the deposit monitoring time came near, small banks had to attract additional deposits by either manipulating the timing of expirations of the WMP products with high prices or offering a much higher deposit rate than the legal ceiling imposed by the PBC. The twin problem of deposit shortfalls and high costs for small banks to attract deposits, as well as other related issues, has been discussed extensively in various Chinese financial newspapers and some Chinese academic articles (Ba et al., 2013, for example).

2.5.4 The Asset Side of Banks' Balance Sheet

As shown in the bottom panel of Figure 2.2, the share of entrusted loans in the sum of entrusted lending and bank lending tripled during the monetary tightening period. According to our micro data, more than 60% of the total amount of entrusted loans was channeled to the risky industry between 2007 and 2013; out of these risky entrusted loans, 77% was facilitated by commercial banks. How such risky entrusted lending was connected with the asset side of the bank's balance sheet is a focus of this section.

As early as 28 May 2010, the PBC and CBRC issued a joint new regulation, called "Notice on Financial Services to Further Support Energy Saving and Eliminate Backward-Production Capacity," to ensure "the soundness of the banking system." The main purpose of this new regulation was to reinforce the earlier laws of prohibiting banks from originating new bank loans to the risky industry. While this and earlier laws made traditional bank loans *safe*, they created their own unforeseen problem.

Because small banks faced much higher costs than large banks, implicit or explicit, in attracting deposits to cope with the LDR regulation risk, small banks had an incentive to reduce bank loans that were subject to the LDR regulation and increase nonloan investment that was *not* subject to the same regulation.

The LDR regulation risk is a unique institutional characteristic of China because the LDR ceiling is set arbitrarily by the PBC. On the asset side of banks' balance sheet, there is one major entry called "account-receivable investment (ARI)," which is an asset not counted as part of bank loans. As our theory in Section 2.4.2 predicts, this nonloan investment can become an effective device for small banks to circumvent both regulations simultaneously: the LDR ceiling and the safe-loan law. But how was ARI on banks' balance sheet related to entrusted loans off balance sheet? When small banks were engaged in risky entrusted lending during the period of 2007-2013, they purchased the beneficiary rights of those loans (entrusted rights), which were recorded in the category of ARI. This nonloan investment category, even though on the asset side of bank's balance sheet, was nonetheless immune from both LDR and safe-loan regulations and thus gave small banks an incentive to funnel risky entrusted loans by either purchasing entrusted rights or offering implicit guarantees to such loans.

Chinese small banks had a penchant for partaking in risky loan activities because their expected returns were higher than those on non-risky loans (see Table 2.19 in Section 2.4.2); as we find in our own empirical study, they were indeed engaged in funneling risky entrusted loans during the period of monetary tightening, more so than large banks. The sharp contrast of small banks to large banks in their risk-taking behavior is manifested by the findings presented in Table 2.14, which reports the correlations of entrusted loans channeled by banks off balance sheet and nonloan investment on balance sheet. For both samples of 2007-2013 and 2010-2013, the correlation between new entrusted loans and changes in ARI is significantly positive for small banks, while the same correlation is statistically insignificant for large banks.

This result holds for changes in $\frac{\text{ARI}}{\text{ARI}+B}$. For large banks, the same correlations are either close to zero or negative without statistical significance.

While the correlations of overall entrusted lending with ARI are positive and significant for small banks but not for large banks, the question is whether this result holds for the correlations of *risky* entrusted lending and ARI. Table 2.15 reports such correlations for the same two periods. Clearly, the estimated correlations for small banks continue to be positive and statistically significant; again, the estimates are statistically insignificant for large banks. This striking finding is confirmed by the government's concern that commercial banks, especially small ones, have taken balance-sheet risks by providing implicit and explicit guarantees to entrusted lending, where the explicit guarantees were in the form of entrusted rights. So grave was the concern that the government in 2014 made it illegal for banks to mask the balance-sheet risk "through the channel of entrusted lending."

The above empirical finding reveals that the linkage between entrusted loans and China's banking system has developed far beyond the basic structure displayed in Figure 2.3. Since traditional loans on banks' balance sheet were largely safe by regulations or by implicit guarantees of the government and since large banks were capable of weathering deposit shortfall with no extra cost, the behavior of large banks described by Figure 2.5 is in essence similar to the basic structure represented by Figure 2.3. The issue, however, lies in the risk-taking behavior of small banks. As shown in Table 2.14, entrusted lending funneled by small banks is significantly and positively correlated with ARI, while the correlation does not exist or may even be negative for large banks. The extensive institutional structure for small banks' activity in entrusted lending is illustrated by Figure 2.6. Because of the disparity between small and large banks in costs of acquiring additional deposits under the pressure of deposit shortfalls, we show in Section 2.4.2 that a combination of the LDR and safe-loan regulations gives small banks a wrong incentive to take on risky nonloan investment through regulatory arbitrage.

2.6 A Theoretical Model Against the Unique Institutional Background

Below we build a tractable equilibrium model, grounded in Chinese institutional details, for understanding how the behavior of Chinese banks influences their optimal portfolio choice under the constraint of both LDR and safe-loan regulations. We then discuss how our model predictions are consistent with our empirical findings.

2.6.1 Environment

There are two types of banks, large and small, distinguished only by the costs of meeting unexpected deposit shortfalls that threaten to violate the LDR ceiling constraint. Although all banks face the same LDR regulation, large banks, being state-owned, pay no extra cost to recoup deposit losses. Small banks, on the other hand, have to pay extra costs to recover temporary deposit shortfalls. There is an aggregate shock that increases a withdrawal risk to deposits in all banks.[20] For simplicity, both large and small banks face the same deposit withdrawal risk, an assumption that is consistent with the evidence provided by the PBC's various Financial Stability Reports on the monthly deposit volatilities across different types of banks.

The bank has three types of assets: (i) cash, (ii) traditional loans (B_t) subject to the safe-loan regulation as well as regulation risks associated with random deposit

[20]This assumption is consistent with the facts presented in Figure 2.1. Aggregate shocks that contract monetary aggregates tend to increase pressures on deposit withdrawals and as a result contract deposits. Our model abstracts from trend growth by assuming that any changes are deviations from trend.

shortfalls, and (iii) risky nonloan assets (I_t^r) subject to the default risk but not to the regulation risks as I_t^r are not counted as part of B_t according to the LDR regulation. Given the deposits, the bank makes an optimal portfolio choice between safe loans and risky assets. Within each period, banking activities for both types of banks involve two stages: a lending stage and a balancing stage.

2.6.2 Lending Stage

At the lending stage, the representative small bank decides how much deposit to demand, how much dividend to distribute, and how to allocate three types of assets for investment: intertemporal safe bank loans (longer term), within-period risky shadow assets (shorter term), and cash.[21] Bank loans, B_t, are safe (default free) but subject to the regulatory constraint on the LDR, and are purchased at a discount price q_t. Risky assets, I_t^r, have a default probability p^r and are purchased at a discount price $0 < q_t^r < 1$.

The law of motion for bank loans evolves as

$$\tilde{B}_t = \delta B_t + S_t, \tag{2.9}$$

where $(1 - \delta)B_t$ represents a fraction of loans that is retired and S_t represents new *safe* loans made by the bank to comply with the safe-loan regulation. Denote cash by C and

$$\tilde{C}_t = C_t + \varphi_t, \tag{2.10}$$

where φ_t represents additional cash holdings chosen by the bank.

[21] The maturities assumed for bank loans and risky assets capture the essence of our empirical finding that risky assets tend to have a shorter maturity than safe assets (see Section 2.4.1). This assumption, along with other assumptions in the rest of the analysis, is made to keep our model tractable for obtaining intuitive results.

At the beginning of the period, the bank's balance-sheet constraint is

$$D_t + E_t = \underbrace{C_t + (1-\delta)B_t}_{\text{new cash}} + q_t\delta B_t, \tag{2.11}$$

where D_t represents deposits and E_t the bank's equity or capital. Table 2.16 or Table 2.17, below, represents the balance sheet in which the left hand column indicates the asset side and the right hand column the liability side.

The bank's balance-sheet constraint, after choosing $\tilde{C}_t$ (or φ_t), I_t^r, $\tilde{B}_t$ (or S_t), $\tilde{D}_t$, and dividend DIV_t, is

$$\tilde{D}_t/R_t^D + E_t - \mathrm{DIV}_t = \tilde{C}_t + q_t^r I_t^r + q\tilde{B}_t \tag{2.12}$$

which leads to

$$\underbrace{\tilde{D}_t/R_t^D}_{\text{deposits}} + \underbrace{E_t - \mathrm{DIV}_t + (1-q_t^r)I_t^r + (1-q_t)\tilde{B}_t}_{\text{equity}} = \underbrace{\tilde{C}_t}_{\text{cash}} + \underbrace{I_t^r + \tilde{B}_t}_{\text{assets}}, \tag{2.13}$$

where R_t^D is the deposit rate. The balance sheet now becomes Table 2.18.

Substituting (2.9), (2.10), and (2.11) into (2.13) gives us the flow-of-funds constraint as

$$\underbrace{\tilde{D}_t/R_t^D - D_t}_{\Delta\text{deposits}} + \underbrace{(1-q_t^r)I_t^r + (1-q_t)S_t - \mathrm{DIV}_t}_{\Delta\text{equity}} = \underbrace{\varphi_t + I_t^r + \left(\tilde{B}_t - B_t\right)}_{\Delta\text{assets}}. \tag{2.14}$$

The standard credit constraint is

$$\tilde{D}_t/R_t^D \leq \kappa\left[E_t - \mathrm{DIV}_t\right], \tag{2.15}$$

where κ is the leverage ratio and the term in brackets after κ represents the equity after the dividend payout.

2.6.3 Balancing Stage

At the balancing stage, two random events occur. First, all banks (large and small) are subject to idiosyncratic withdrawal shocks to deposits. The idiosyncratic risk is represented by ω_t such that

$$\omega_t = \begin{cases} \omega^h & \text{with probability } p_t^\omega \\ \omega^l & \text{with probability } 1 - p_t^\omega \end{cases}, \tag{2.16}$$

where $\omega^h > \omega^l$. To obtain a closed-form solution for intuitive results, we simplify the withdrawal risk distribution (2.16) by letting $\omega^h = 1$ and $\omega^l = 0$.Second, risky assets are defaulted with probability p^r.

The amount of bank loans is subject to the LDR regulation as

$$q_t \tilde{B}_t \leq \theta \frac{(1 - \omega_t) \tilde{D}_t}{R_t^D},$$

where θ is the LDR ceiling set by the PBC. Denote

$$\tilde{x}_t = q_t \tilde{B}_t - \theta \frac{(1 - \omega_t) \tilde{D}_t}{R_t^D} \tag{2.17}$$

and

$$\chi(\tilde{x}_t) = \begin{cases} r_t^b \tilde{x}_t & \text{if } \tilde{x}_t \geq 0 \\ 0 & \text{if } \tilde{x}_t < 0 \end{cases},$$

where $r_t^b > 0$ is the extra cost of obtaining additional deposits $\tilde{x}_t$. For clear illustration, we assume $r_t^b = 0$ for large banks to capture the fact that these banks can weather deposit fluctuations with no extra costs. It is straightforward to show that large banks' portfolio choice is indifferent to safe loans and risky investment (after adjusting for the risk premium). Thus, the rest of the analysis is about small banks. Unless indicated otherwise, the word "bank" is shorthand for "small bank" in Section 2.4.2.

If default on I_t^r (risky assets) does not occur (in the no-default state), one can derive from equation (2.13) the balance-sheet constraint for the bank as

$$\underbrace{\tilde{D}_t/R_t^D - I_t^r}_{\text{debt reduction}} + \underbrace{E_t - \mathrm{DIV}_t + (1-q_t^r)I_t^r + (1-q_t)\tilde{B}_t}_{\tilde{E}_t\text{: equity}} = \underbrace{\tilde{C}_t + \tilde{B}_t}_{\text{assets}}. \tag{2.18}$$

If I_t^r is defaulted (in the default state), the bank's balance-sheet constraint becomes

$$\underbrace{\tilde{D}_t/R_t^D}_{\text{liabilities}} + \underbrace{E_t - \mathrm{DIV}_t - q_t^r I_t^r + (1-q_t)\tilde{B}_t}_{\tilde{\tilde{E}}_t\text{: equity}} = \underbrace{\tilde{C}_t + \tilde{B}_t}_{\text{assets}}. \tag{2.19}$$

Since $\tilde{\tilde{E}}_t = \tilde{E}_t - I_t^r$, the bank's equity is reduced in the default state. At the end of period t (the beginning of period $t+1$), the stock variables are balanced as

$$D_{t+1} = \tilde{D}_t(1-\omega_t) + \chi(\tilde{x}_t) - \frac{\varepsilon_t R_{t+1}^D I_t^r}{q_t^r}, \tag{2.20}$$

$$C_{t+1} = \tilde{C}_t - \omega_t \tilde{D}_t, \tag{2.21}$$

$$B_{t+1} = \tilde{B}_t, \tag{2.22}$$

where

$$\varepsilon_t = \begin{cases} 1 & \text{with probability } 1-p^r \text{ (the no-default state)} \\ 0 & \text{with probability } p^r \text{ (the default state)} \end{cases}.$$

2.6.4 The Bank's Optimizing Problem

The bank's optimizing problem is complex. To maintain tractability, we simplify the liability-side behavior as it is not a focus of our model.[22] The asset-side story, motivated by China's institutional arrangements and our empirical evidence, is a central piece of our theory. To avoid notational glut and make our theory transparent, we omit the time subscript whenever no confusion arises. The optimizing behavior at the lending stage can thus be described as

$$V^l\left(C, B, D; z\right) = \max U(\mathrm{DIV}) + E_{\omega,\varepsilon}\left[V^b(\tilde{C}, \tilde{B}, \tilde{D}; z)\right],$$

where $z = \{r^b, p^\omega, q, q^r, R^D\}$, V^l is the value function at the lending stage, V^b is the value function at the balancing stage, and $E_{\omega,\varepsilon}$ is the mathematical expectation with respect to the (ω, ε) measure. By choosing $(\mathrm{DIV}, \varphi, S, I^r)$, the bank solves the above problem subject to

$$\tilde{D}/R_t^D = D - (1-\delta)B + \mathrm{DIV} + \varphi + q^r I^r + qS, \tag{2.23}$$

$$\tilde{C} = C + \varphi, \tag{2.24}$$

$$\tilde{B} = \delta B + S, \tag{2.25}$$

$$\tilde{D}/R^D \leq \kappa\left[\tilde{C} + q^r I^r + q\tilde{B} - \tilde{D}/R^D\right], \tag{2.26}$$

where constraint (2.23) corresponds to (2.14); and constraint (2.26), derived from (2.13) and (2.15), represents the credit constraint on the bank's optimization problem.

The balancing-stage behavior can be described as

$$V^b(\tilde{C}, \tilde{B}, \tilde{D}; z) = \beta E_M\left[V^l(C', B', D'; z') \mid z\right]$$

[22] See Hachem and Song (2015) for a detailed modeling of the bank's liabilities.

subject to

$$D' = (1-\omega)\tilde{D} + \chi(\tilde{x}) - \frac{\varepsilon R^{D\prime} I^r}{q^r}, \tag{2.27}$$

$$C' = \tilde{C} - \omega\tilde{D}, \tag{2.28}$$

$$B' = \tilde{B}, \tag{2.29}$$

$$\tilde{x} = q\tilde{B} - \theta(1-\omega)\tilde{D}/R^D, \tag{2.30}$$

where β is a subjective discount factor, $z' = \{r^{b\prime}, p^{\omega\prime}, q', q^{r\prime}, , R^{D\prime}\}$, and E_M represents the mathematical expectation with respect to macroeconomic factors such as the risk of deposit withdrawal. Such factors determine how z' evolves conditioning on the realization of z. Constraints (2.27), (2.28), and (2.29) correspond to (2.20), (2.21), and (2.22); constraint (2.30) corresponds to (2.17).

Combining the two stages, we can describe the overall optimization problem as

$$\begin{aligned} V^l(C,B,D;z) = &\max U(\mathrm{DIV}) \\ &+ \beta E_{M,\omega,\varepsilon}\left[V^l\left(\tilde{C}-\omega\tilde{D}, \tilde{B}, (1-\omega)\tilde{D} + \chi(\tilde{x}) - \frac{\varepsilon R^{D\prime} I^r}{q^r}; \tilde{z}\right) \mid z\right] \end{aligned} \tag{2.31}$$

subject to (2.23), (2.24), (2.25), and (2.26). The choice variables for this optimization are $(\mathrm{DIV}, \varphi, S, I^r)$. Given $E = C + q\delta B - (D - (1-\delta)B)$, we have the following proposition:

*Proposition 1.*The optimization problem (2.31) can be simplified and collapsed into the single-state representation

$$V(E;z) = \max U(\mathrm{DIV}) + \beta E_{M,\omega,\varepsilon}\left[V(E';z') \mid z\right] \tag{2.32}$$

subject to (2.26), (2.30), and

$$E - \mathrm{DIV} = \underbrace{\tilde{C}}_{\text{cash}} + \underbrace{q^r I^r + q\tilde{B}}_{\text{assets}} - \underbrace{\tilde{D}/R^D}_{\text{liabilities}}, \tag{2.33}$$

$$E' = \underbrace{\tilde{C} - \omega\tilde{D}}_{\text{cash}} + \underbrace{q'\delta\tilde{B} + (1-\delta)\tilde{B}}_{\text{assets}} - \underbrace{\left[(1-\omega)\tilde{D} + \chi(\tilde{x}) - \frac{\varepsilon R^{D\prime} I^r}{q^r}\right]}_{\text{liabilities}}, \tag{2.34}$$

where the single state is E, (2.33) corresponds to (2.12), (2.34) is derived from (2.11), (2.20), (2.21), and (2.22) (by moving time t in (2.11) forward to time $t+1$), and the choice variables are $(\mathrm{DIV}, \tilde{C}, \tilde{B}, \tilde{D}, I^r)$.

Proof. See Appendix ■ .

Since constraints (2.26), (2.33), and (2.34) are linear in E and the objective function is homothetic in E, the solution to the bank's problem not only exists but also is unique and the policy function is linear in equity E. Moreover, thanks to the Principle of Optimality, the bank's dynamic problem can be separated into two subproblems, one concerning an intertemporal choice of dividend payoffs and the other relating to an intratemporal portfolio allocation. The following proposition formalizes these two results.[23]

Proposition 2. Let

$$U(\mathrm{DIV}) = \frac{\mathrm{DIV}^{1-\gamma}}{1-\gamma},$$

where $\gamma \geq 1$. Optimization problem (2.32) satisfies the two properties: homogeneity in E and separability of portfolio choice from dividend choice.

- **Homogeneity**. The value function $V(E; z)$ is

$$V(E; z) = v(z)E^{1-\gamma},$$

[23] The homogeneity and separability properties in Proposition 2 are similar to Bianchi and Bigio (2014).

and $v(z)$ satisfies the Bellman equation over the choice variables $\{\text{div}, \tilde{c}, i^r, \tilde{b}, \tilde{d}\}$

$$v(z) = \max U(\text{div}) + \beta E_{M,\omega,\varepsilon}\left[v(z')\ \left(e'(\omega,\varepsilon;z',z)\right)^{1-\gamma} \mid z\right] \tag{2.35}$$

subject to

$$\tilde{d}/R^D \leq \kappa\left[\tilde{c} + q^r i^r + q\tilde{b} - \tilde{d}/R^D\right], \tag{2.36}$$

$$1 = \tilde{c} + \text{div} + q^r i^r + q\tilde{b} - \tilde{d}/R^D, \tag{2.37}$$

$$e' = \tilde{c} + (q'\delta + 1 - \delta)\tilde{b} - \tilde{d} - \chi\left(q\tilde{d} - \theta(1-\omega)\tilde{d}\right) + \frac{\varepsilon R^{D\prime} i^r}{q^r}, \tag{2.38}$$

where

$$\left[\text{div}, \tilde{c}, \tilde{b}, \tilde{d}, i^r, e'\right] = \frac{\left[\text{DIV},\ \widetilde{C}, \widetilde{B}, \widetilde{D}, I^r, E'\right]}{E}. \tag{2.39}$$

- **Separability**. Problem (2.35) can be broken into two separate problems. The first problem is for banks to make an optimal portfolio choice, by choosing $\{w_c, w_i, w_b, w_d\}$ to maxmize the certainty-equivalent portfolio value, described as

$$\Omega(z', z) = \max\{E_{\omega,\varepsilon s}\left[w_c + R^I w_i + R^B w_b - R^D w_d - R^x\right]^{1-\gamma}\}^{\frac{1}{1-\gamma}} \tag{2.40}$$

subject to

$$1 = w_c + w_i + w_b - w_d, \tag{2.41}$$

$$w_d \leq \kappa(w_c + w_i + w_b - w_d), \tag{2.42}$$

and taking the following prices as given

$$R^I = \frac{\varepsilon R^D}{q^r},\ R^B = \frac{q' + 1 - \delta}{q},\ R^x = \chi\left(w_b - \theta(1-\omega)w_d\right), \tag{2.43}$$

where

$$w_\varsigma = \frac{\varsigma}{1 \ - \ \text{div}}, \text{ for } \varsigma = \tilde{c}, \tilde{d}/R, q^r i^r, q\tilde{b}.$$

The second problem is to choose div in response to aggregate shocks, described as

$$v(z) = \max_{\text{div}} U(\text{div}) + \beta(1-\text{div})^{1-\gamma} E_M \left[\Omega(z', z)^{1-\gamma} v(z') \,|\, z \right]. \tag{2.44}$$

Proof. See Appendix .■

Note that equations (2.36), (2.37), and (2.38) are derived from equations (2.26), (2.33), and (2.34) and that e' is a function of ω, ε, z', and z such that

$$e'(\omega, \varepsilon; z', z) = (1-\text{div}) R^E (\omega, \varepsilon; z', z), \tag{2.45}$$

where R^E is the return to bank's equity after divident payout

$$R^E (\omega, \varepsilon; z', z) = w_c + R^I w_i + R^B w_b - R^D w_d - \chi (w_b - \theta(1-\omega) w_d). \tag{2.46}$$

Proposition 2 breaks the potentially unmanageable problem into two tractable problems by separating dividend decision about DIV in response to aggregate shocks from portfolio choice about φ, S, I^r, and $\tilde{D}$ in response to idiosyncratic risks. This technical advancement enables us to establish the following substantive proposition.

Proposition 3. As p^ω increases, the bank's optimal portfolio choice is such that

(i) the share of risky assets in total assets $\frac{q^r I^r}{q^r I^r + qB'}$ increases, i.e., $\partial \frac{q^r I^r}{q^r I^r + qB'} / \partial p^\omega > 0$;

(ii) the amount of risky assets $q^r I^r$ increases, i.e., $\partial (q^r I^r) / \partial p^\omega > 0$.

Proof. See Appendix.■

The theory developed thus far, especially Proposition 3, provides a coherent explanation of the "conspicuous phenomenon" illustrated by Figure 2.2. It also provides a general and tractable framework for studying the optimal but risk-taking behavior of small banks. According to Proposition 3, the optimal portfolio decision leads to an increase of investment in risky assets under monetary tightening for small banks and thus provides a theoretical underpinning of our empirical findings. The intuition for this powerful result comes from the asset-pricing equation governing a tradeoff between safe bank loans and risky nonloan investment[24]

$$E_\varepsilon(R^I) - \underbrace{\left[-\frac{\mathrm{Cov}_\varepsilon\left(R^I, E_\omega(R^E)^{-\gamma}\right)}{E_\varepsilon\left[E_\omega(R^E)^{-\gamma}\right]} \right]}_{\text{default risk premium}} = R^B - \underbrace{E_\omega\left[R^x_b(w_b, w_d; \omega)\right]}_{\text{expected regulation cost}}, \tag{2.47}$$

where $R^x_b(w_b, w_d; \omega)$ is the partial derivative of $R^x(w_b, w_d; \omega)$ with respect to safe loans:

$$R^x_b(w_b, w_d; \omega) = \frac{\partial R^x(w_b, w_d; \omega)}{\partial w_b}.$$

In the asset-pricing equation (2.47), the left-hand-side term is the expected return on risky investment, adjusted for the risk premium due to the default risk. The right-hand-side term is the expected return on safe bank loans, adjusted for the expected regulation cost. The risk premium is always positive. The expected regulation cost, also positive, is the expected marginal cost associated with the lending amount B subject to the LDR regulation. This term captures the extra cost of recovering deposit shortfalls. When the risk of deposit shortfalls rises, the expected regulation cost increases and so does the return on risky investment relative to the return on bank loans. Thus, small banks have an incentive to rebalance the portfolio by increasing the share of risky assets in total assets.

For the asset-pricing equation (2.47) to hold, the necessary and sufficient condition

[24]See Appendix 2.8 for the derivation of this condition.

is

$$E_\varepsilon(R^I) > R^B - r^b p^w, \tag{2.48}$$

where $r^b p^w = E_\omega(R^x_b)$ is the expected regulation cost. Equation (2.48) states that the expected return on risky investment is greater than the effective return on bank loans such that the bank has an incentive to invest in risky assets, even if the bank is risk-averse. Thus, the asset-pricing equation implies that it is optimal for the bank to increase the share of risky assets in its total investment on the asset side of the balance sheet.

only does theory predict a rise of the share of risky assets for any fixed amount of total investment, it also predicts another powerful result: investment in risky assets increases in absolute terms. The proof of this result is more involved (see Appendix 2.8), but the intuition can be clearly laid out. Consider a low deposit rate such that

$$R^D < R^B - r^b p^w. \tag{2.49}$$

That is, the borrowing cost R^D is lower than the effective return on bank loans. The low borrowing cost is a unique Chinese institutional feature that the deposit rate imposed by the government was kept artificially low.[25] Such a low borrowing cost makes it optimal for the bank to leverage to the maximum; as a result, the credit constraint (2.15) or (2.26) is always binding. In our theoretical model, when the risk to deposit withdrawal increases at the lending stage, the expected net return for leverage adjusted for the risk premium becomes greater than R^D (see equations (2.48) and (2.49)). It is therefore profitable to borrow as much as possible by increasing $\tilde{D}$ until the credit constraint binds. The resource from the increased borrowing goes to risk assets to compensate for the costs associated with actual withdrawals in the balancing stage.

[25] On 23 October 2015 the PBC decided to remove the deposit rate ceiling.

Economically, when the income effect of a reduction in the expected return on equity ($E_{\omega,\varepsilon} R^E$) due to an increase in the expected regulation cost dominates the corresponding substitution effect (the substitution between today's and tomorrow's dividend payoffs), it is optimal for the small bank to raise risky investment to compensate extra costs of recouping deposit losses. This can be seen from (2.12) in which the left-hand-side term increases because DIV_t falls. This increase, together with the increase in the share of risky assets in response to monetary tightening, implies that $q_t^r I_t^r$ must increase.

In summary, the amount of risky investment increases during the period of monetary tightening because risky investment is an effective tool to compensate an increase in the expected regulation cost due to unexpected deposit losses. By purchasing entrusted rights the small bank receives a higher expected return on this nonloan investment, thereby killing two birds with one stone as discussed in the Introduction. In effect, investment in risky nonloan assets allows the small bank to exploit regulatory arbitrage because this risky investment is not subject to the safe-loan regulation that explicitly bans bank lending to the risky industry nor to the LDR regulation.

2.6.5 Further Discussions

In the above theory, the necessary and sufficient condition for small banks to increase investment in risky assets relative to safe loans is

$$E_\varepsilon(R^I) > R^B - \text{Expected regulation cost.}$$

That is, the expected return to risk assets must be greater than the effective return on bank loans. This important condition is supported by the data reported in Table 2.19, whereby the interest rate on risky entrusted loans was substantially higher than the interest rate on non-risky entrusted loans, which in turn was higher than the interest rate on bank loans in 2007-2013 and in 2010-2013. The interest rate on bank loans is the one-year base lending rate set by the PBC. The reported interest rates on entrusted loans, risky or not, are not adjusted for maturity or the term premium. The interest rate spread between risky entrusted lending and bank lending, however, has a similar magnitude after we control for maturity by using a method similar to equation 2.1.

There are two competing hypotheses about the effect of entrusted lending. The first hypothesis that banks were supposed to act only as trustees or middlemen without bearing any credit risks on their balance sheet as indicated in Figure 2.3. This hypothesis was true only on paper, but in practice banks, especially small banks, were prone to funnel risky entrusted loans during the period of monetary tightening. Our empirical and institutional analyses support a competing hypothesis that such a risk-taking perchant for funneling entrusted loans to the real estate and overcapacity industries threatened the health of the banking system. The size of small banks as a whole was no small potatoes; the capital size (equity) of small banks as a whole accounted for 39% of the total capital for all commercial banks for the periods 2007-2013 and 2010-2013. Figure 2.3 describes the mechanism of how the risks were transmitted to small banks' balance sheet through shadow loans. As discussed in Section 2.4.2, it is the unique institutional asymmetry between large and small banks that made a Chinese small bank willing to take on risky investment. This asymmetry is precisely the difference between large and small banks in costs of meeting deposit shortfalls when there are aggregate negative shocks that cause unexpected declines in deposits.

The risk spillover from shadow loans to banks' balance sheet began to be recognized by both G20's Financial Stability Board and various Chinese authorities in late 2013 and early 2014.[26] Their concerns about the spillover were so grave that the Chinese government took concrete steps after the first quarter of 2014, by issuing and then implementing new regulations specifically designed to curb the risk-taking behavior of banks' participation in entrusted lending. On 29 April 2014 the CBRC held a state-wide official meeting on "Financial and Economic Analyses," identifying "nonstandard assets" as a threat to the health of the financial system and specifically outlining steps in containing the riskiness of entrusted lending and entrusted rights in the banking system.[27] In particular, the specific rules outlined in the meeting prohibit banks from providing implicit or explicit guarantees of risky entrusted lending and from purchasing entrusted rights.

The cost disparity between large and small banks in attracting additional deposits under the pressure of deposit shortfalls against the LDR regulation is part of the driving force in our theory of the benefit of increasing nonloan investment in risky assets through regulatory arbitrage. The decree "Notice No. 236: On Strengthening Commercial Banks' Deposit Stability Management" jointly issued on 12 September 12 by the CBRC, the Ministry of Finance, and the PBC effectively banned the practice of small banks in acquiring additional deposits through the WMP channel, by offering higher deposit rates, or through other high-cost means. Perhaps realizing that this practice was not the only problem, the State Council passed a draft of the "People's Republic of China Commercial Bank Amendment Act" on 24 June 2015 to remove the LDR ceiling and thus officially ended this regulation that was enacted in 1995.

With all these changes, many more new regulations were enacted in 2015 for the purposes of insulating the banking system from being endangered by risky entrusted lending and more generally risky shadow banking. Yet the average capital adequacy ratio between 2010 and 2013 was almost the same for both large and small banks.

[26]In 2009 the G20 countries created the Financial Stability Board from their previous financial stability forum to promote the goal of achieving global financial stability.

[27]Nonstandard assets include the WMPs, interbank businesses, trusted loans, entrusted loans, and investment in nonstandard claims (for example, entrusted rights purchased by banks).

On paper all Chinese banks met, by a large margin, the capital requirement (8%) set by Basel III. A deeper analysis reveals a different story: risk weights assigned in calculation of the capital ratio may not adequately reflect the degree of riskiness expressed by China's various new regulations. For example, Basel III rules give a risk weight of 1250% to asset backed securities or structure securities to avoid the systemic risk. By contrast, Chinese banks assign only a 100% risk weight to ARI, the same weight as that assigned to regular corporate loans. One can argue that entrusted rights in the category of ARI is in essence equivalent to an asset-backed security issued by lending firms with entrusted loans as backing assets. It is therefore likely that the risk weight for entrusted rights does not fully capture the degree of riskiness borne by such assets. With proper risk weights, the LDR and safe-loan regulations should be removed all together and the institutional asymmetry would have no place in helping create a wrong incentive for small banks, as illustrated by Figure 2.7. Future research on a proper regulatory design of risk weights for different categories of assets in Chinese banks, therefore, would prove fruitful and important to avoid the systemic risk.

2.7 Conclusion

Using our constructed micro data, we establish evidence that banks actively engaged in channeling risky entrusted loans during the period of monetary contractions. We argue that the LDR regulation, coupled with regulations prohibiting banks from making traditional loans to the risky industry, created an incentive for small banks to bring the risk of shadow loans into their balance sheet through regulatory arbitrage to compensate high costs of meeting random deposit shortfalls. Our study is a positive analysis, which delivers a concrete example of how well-intended regulations can lead to wrong incentives that may endanger the health of the banking system through shadow banking.

The period of monetary tightening and regulatory restrictions on commercial banks in our 2007-2013 sample offers a natural experiment to provide a positive analysis on the linkages between monetary policy, shadow banking, and traditional banking. Our empirical and theoretical findings demonstrate that banks' risk-taking behavior in funneling shadow loans was not just an isolated incident, but rather it foreshadowed how banks effectively used regulatory arbitrage to take on risks both on and off balance sheet. In particular, our positive analysis highlighted two specific loopholes of China's regulatory design that contributed to such risk-taking behavior.[28]

Since 2014 the Chinese government has taken concrete steps to enact and implement a host of new regulations in an effort to close such loopholes. In particular, these regulations prohibit banks from taking risks in entrusted lending either on or off balance sheet, to ban banks from paying higher prices than what regulations allowed to meet deposit shortfalls, and finally to remove the decades-long LDR regulation all together. In the context of these new and vigorous regulations, our positive study begets new and challenging normative questions. What is an effective and efficient way for the government to remove the institutional asymmetry between small and large banks? How should the government assign risk weights to various categories of assets, including securitized assets, in the capital requirement that accord with Basel III to avoid the systemic risk? How should the banking system be so reformed that commercial banks have a correct incentive to price the risks properly, especially those reflecting the risks specific to the Chinese economy?[29] How should the regulators design an ambitious and comprehensive package of regulations for creating right in-

[28]There may be other potential regulatory loopholes that have allowed banks to mask credit risks by entrusted lending. A recent regulation called "On Commercial Banks' Practices of Managing Entrusted Lending: Open for Public Comment," issued by the CBRC on 16 January 2015, is an attempt to prohibit commercial banks from taking on credit risks through various means.

[29]In reality, although we observe that the interest rate charged to the risky industry is higher than the rate charged to other industries, the pricing might still fail to capture fully the underlying default risks due to implicit government guarantees to either banks or risky industries.

centives for commercial banks to invest and lend? How should the government design regulatory tools that are capable of taking into full account how the risks associated with individual banks might potentially cause the systemic financial risk triggered by, for example, the bank panic or fire sales of shadow assets. And how should monetary policy coordinate with regulatory policy in achieving an efficient but stable financial system? These and other important questions will undoubtedly enlarge the scope of this research and we hope that the steps taken in this paper will help foster further research on the effects of monetary and regulatory policies.

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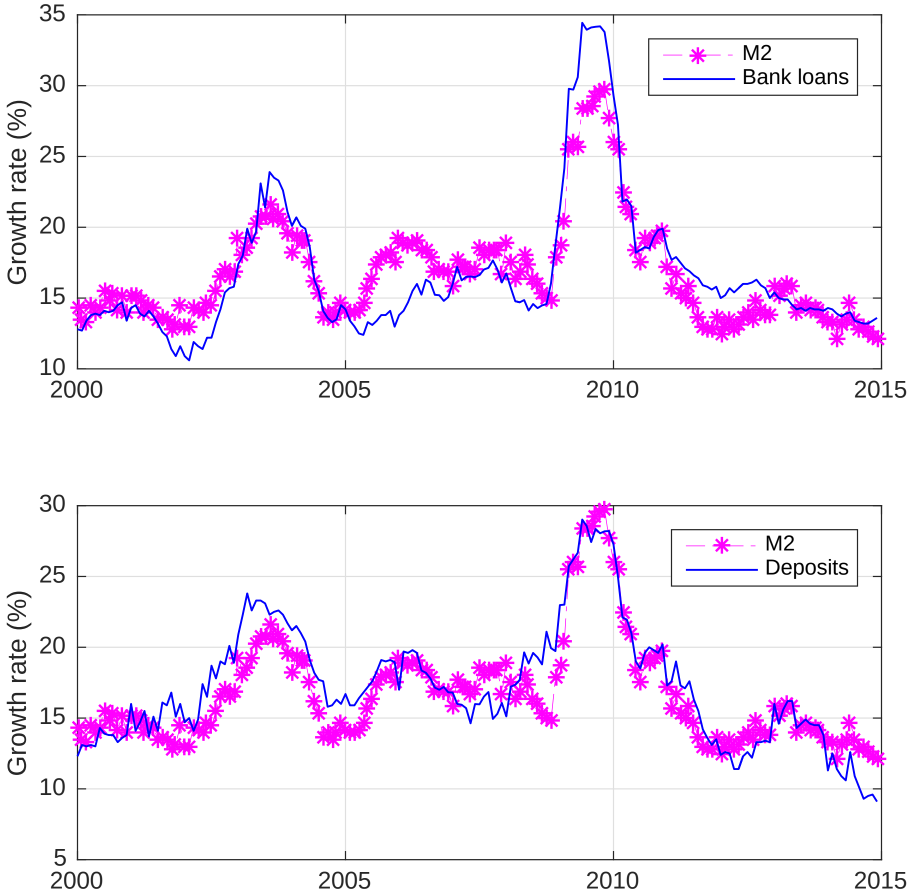
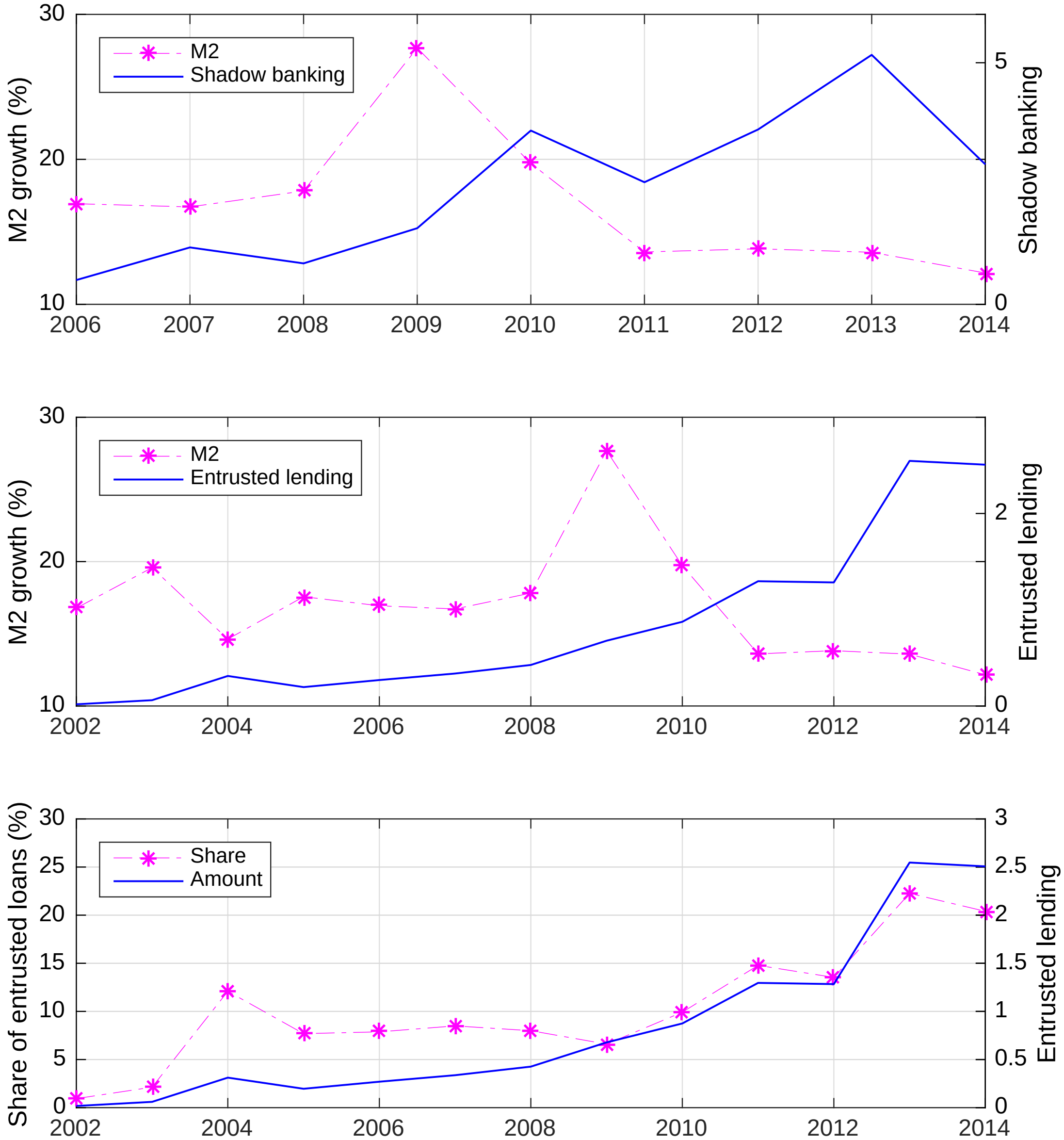
Figure 2.1: Growth Rates (year over year) of Monetary Aggregates, Bank Loans, and Bank Deposits



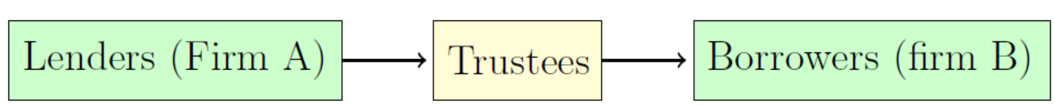
Data sources: PBC and CEIC (the database provided by China Economic Information Center, now belonging to the Euromoney Institutional Investor Company).

Figure 2.2: M2 growth and the rise of shadow banking and entrusted lending (in trillion RMB)



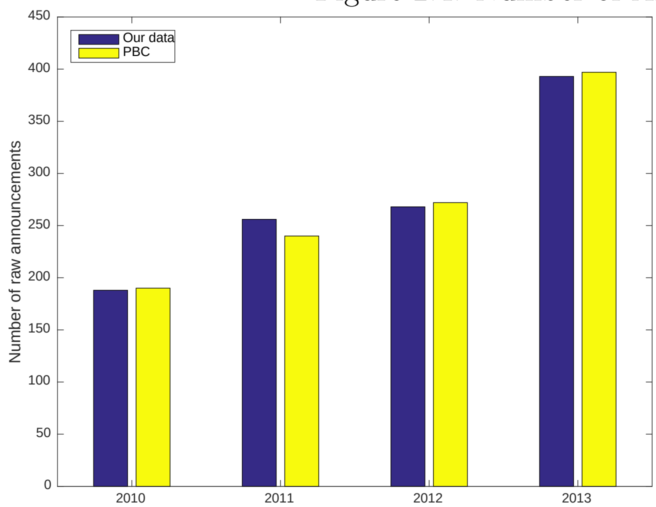
Entrusted lending is one principal component of shadow banking. Both shadow banking and entrusted lending are newly originated loans. The share of entrusted loans is the share of the entrusted-lending amount in the sum of entrusted lending and bank lending, where bank lending is measured by newly originated bank loans as well. Data sources: PBC and CEIC.

Figure 2.3: A Basic Structure of Entrusted Loans as Commonly Understood



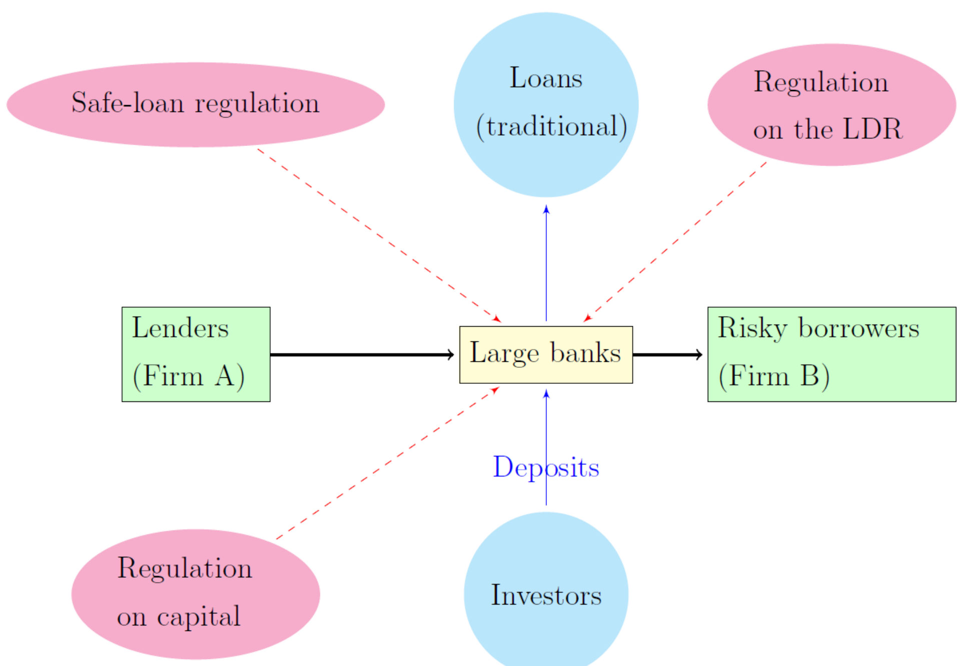
Note: Trustees include banks and nonbank nancial companies that facilitate entrusted loans.

Figure 2.4: Number of Announcements



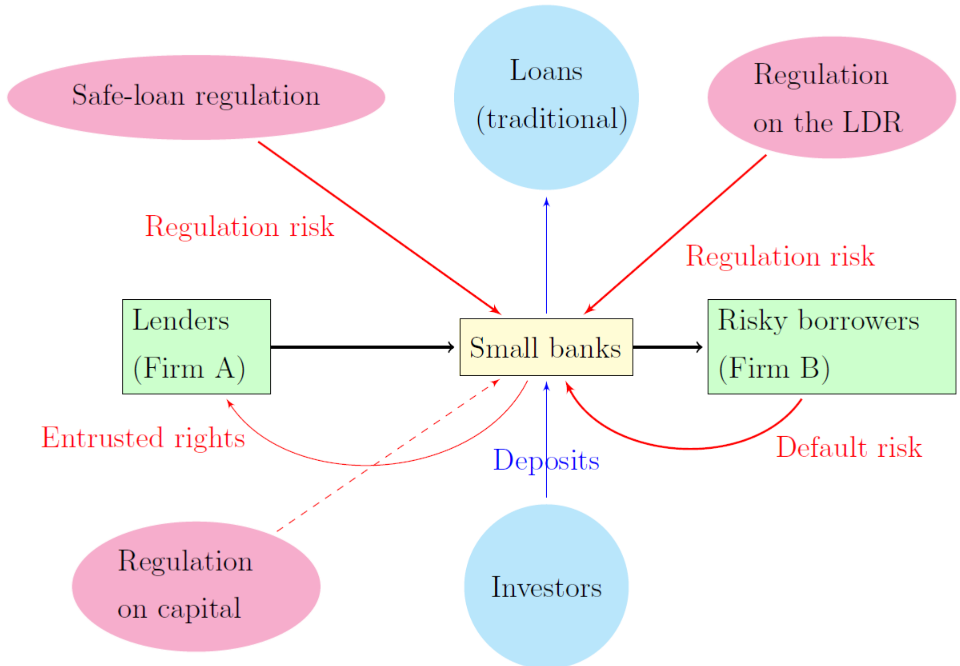
Note: Number of raw announcements we collect versus number published by the PBC's Financial Stability Reports. Data source: WIND

Figure 2.5: An illustration of the Chinese Institutions for Entrusted Loans: How Large Banks Channeled Entrusted Loans



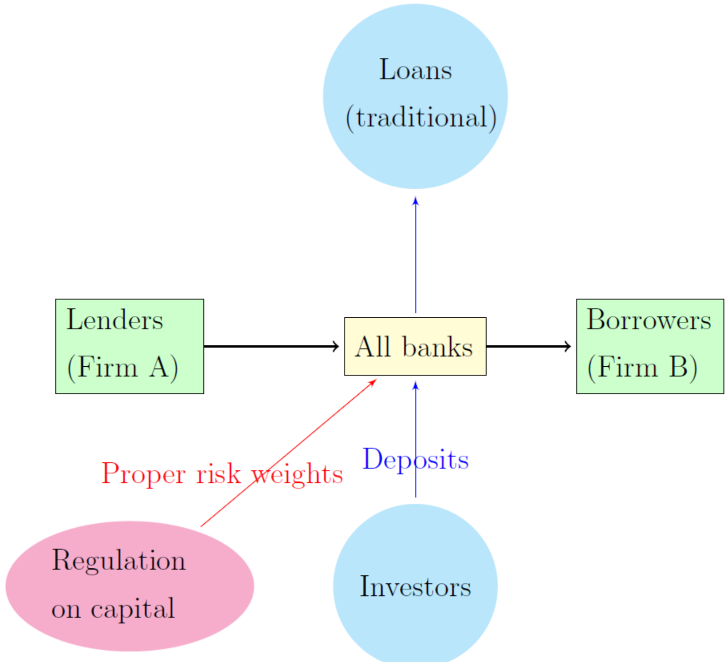
Note: "Safe-loan regulation" refers to a series of 2010-2013 laws that strictly banned commercial banks from expanding bank loans to the risky industry. The dashed lines originating from \Regulation on capital" and \Safe-loan regulation" indicate that these two regulations are far from binding. The dashed line originating from \Regulation on the LDR" indicates that there is no extra cost to comply with this regulation. See Section VI.5 for further discussions.

Figure 2.6: An illustration of the Chinese Institutions for Entrusted Loans: How Small Banks Funneled Entrusted Loans and What Were the Associated Risks



Note:“Entrusted rights” refers to investment in purchases of beneciary rights of entrusted loans. \Safe-loan regulation” refers to a series of 2010-2013 laws that strictly banned commercial banks from expanding bank loans to the risky industry. The dashed line indicates that the current capital requirement regulation is far from binding. See Section VI.5 for further discussions.

Figure 2.7: Risk Weights



Note: An illustration of how to regulate commercial banks with proper risk weights on dierent categories of assets as Chinese banks continue to facilitate entrusted loans as middlemen.

Table 2.1: Number of Announcements Made by Lenders and Borrowers

Description	NLA	NBA	NLABA	Total
Number of observations	644	134	-3	775

Note. NLA: number of lenders' announcements; NBA: number of borrowers' announcements; NLABA: number of the same transactions announced by both lenders and borrowers.

Table 2.2: A Breakdown of The Total Number of Transactions by Types Of Trustees and Types of Loans

Description	NBTs	Large banks	Small banks	Total
Non-affiliated loans	3	87	135	225
Affiliated loans	122	188	240	550
Total	125	275	375	775

Note. NBTs: nonbank trustees.

Table 2.3: Proportions (%) of Loan Transactions and Loan Volume According to Different Types Of Trustees

Description	NBTs	Large banks	Small banks	Total
Number of transactions	16.13	35.48	48.39	100
Loan volume	24.33	34.85	40.82	100

Note. NBTs: nonbank trustees.

Table 2.4: Estimated Results of Regression (1)

Explanatory variable	Coefficient	(Std. Err.)
$\mathfrak{m}_s : \alpha_m$	$-.04\%^{***}$	(.01%)
$\mathscr{I}\,(\text{Risky}_i) : \alpha_r$	$1.28\%^{***}$	(.30%)
Impact of a one-year longer maturity on the spread: $12 * \alpha_m$	$-0.46\%^{***}$	pv=0.00
The estimate spread between risky and non-risky loan rates: α_r	$1.28\%^{***}$	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. The abbreviation "pv" stands for p-value.

Table 2.5: Estimated Results of Regression (2)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	1.85	(2.77)
$g_{t-1}\mathscr{I}\left(\mathrm{Bank}_b\right) : \beta_b$	-6.05^{**}	(2.86)
Impact of money growth via NBTs: α_g	1.85	pv=0.51
Impact of money growth via banks: $\alpha_g + \beta_b$	-4.20^{***}	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation "pv" stands for p-value.

Table 2.6: Estimated Results of Regression (3)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	1.92	(2.78)
$g_{t-1}\mathscr{I}\,(\text{Large}_b) : \beta_\ell$	-4.63	(3.10)
$g_{t-1}\mathscr{I}\,(\text{Small}_b) : \beta_s$	-7.15^{**}	(2.98)
Impact of money growth via NBTs: α_g	1.92	pv=0.48
Impact of money growth via large banks: $\alpha_g + \beta_\ell$	-2.71	pv=0.12
Impact of money growth via small banks: $\alpha_g + \beta_s$	-5.23^{***}	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation "pv" stands for p-value.

Table 2.7: Estimated Results of Regression (4)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	-5.52^{*}	(2.88)
$g_{t-1}\mathscr{I}\left(\text{Risky}_i\right) : \gamma_n$	5.66^{**}	(2.42)
$g_{t-1}\mathscr{I}\left(\text{Bank}_b\right) : \beta_b$	2.95	(2.68)
$g_{t-1}\mathscr{I}\left(\text{Bank}_b\right)\mathscr{I}\left(\text{Risky}_i\right) : \gamma_b$	-4.01^{**}	(1.67)
Impact of money growth on *risky loans* via NBTs: $\alpha_g + \gamma_n$	0.14	pv=0.96
Impact of money growth on *risky loans* via banks: $\alpha_g + \beta_b + \gamma_b$	-6.58^{***}	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation "pv" stands for p-value.

Table 2.8: Estimated Results of Regression (5)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	-5.21^{*}	(2.87)
$g_{t-1}\mathscr{I}\,(\text{Risky}_i) : \gamma_n$	5.25^{**}	(2.39)
$g_{t-1}\mathscr{I}\,(\text{Large}_b) : \beta_\ell$	2.63	(2.85)
$g_{t-1}\mathscr{I}\,(\text{Small}_b) : \beta_s$	2.66	(2.82)
$g_{t-1}\mathscr{I}\,(\text{Large}_b)\,\mathscr{I}\,(\text{Risky}_i) : \gamma_\ell$	-2.70^{*}	(1.69)
$g_{t-1}\mathscr{I}\,(\text{Small}_b)\,\mathscr{I}\,(\text{Risky}_i) : \gamma_s$	-5.02^{***}	(1.81)
of money growth on *risky loans* via NBTs: $\alpha_g + \gamma_n$	0.04	pv=0.99
Impact of money growth on *risky loans* via large banks: $\alpha_g + \beta_\ell + \gamma_\ell$	-5.28^{**}	pv=0.03
Impact of money growth on *risky loans* via small banks: $\alpha_g + \beta_s + \gamma_s$	-7.57^{***}	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation "pv" stands for p-value.

Table 2.9: Relevant Effects to be Controlled

Control variable	Regression						
	(2.2)	(2.3)	(2.4)	(2.5)	(2.6)	(2.7)	(2.8)
GDP_{t-1}: macroeconomic effect	X	X	X	X	X	X	X
Inf_{t-1}: macroeconomic effect	X	X	X	X	X	X	X
$\mathscr{I}(\text{Bank}_b)$: trustee type	X		X				
$\mathscr{I}(\text{Large}_b)$: trustee type		X		X			X
$\mathscr{I}(\text{Small}_b)$: trustee type		X		X		X	X
$\mathscr{I}(\text{Risky}_i)$: borrower type			X	X	X	X	X
α_{sec}: industry fixed effect			X	X	X	X	X
$\mathscr{I}(\text{Risky}_i)\,\mathscr{I}(\text{Bank}_b)$: double interactions			X				
$\mathscr{I}(\text{Risky}_i)\,\mathscr{I}(\text{Large}_b)$: double interactions				X			X
$\mathscr{I}(\text{Risky}_i)\,\mathscr{I}(\text{Small}_b)$: double interactions				X		X	X

Note. "X" indicates that the corresponding fixed effect is included. Regression (2.5) is the benchmark regression.

Table 2.10: Estimated results of regression (6)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	-2.31	(1.56)
$g_{t-1}\mathscr{I}\,(\text{Risky}_i) : \gamma_r$	0.93	(2.01)
Impact of money growth on non-risky loans via banks: α_g	-2.31	pv=0.14
Impact of money growth on *risky loans* via banks: $\alpha_g + \gamma_r$	-1.38	pv=0.41

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation "pv" stands for p-value.

Table 2.11: Estimated Results of Regression (7)

Explanatory variable	Coefficient	(Std. Err.)
$g_{t-1} : \alpha_g$	-1.93	(1.98)
$g_{t-1}\mathscr{I}(\text{Risky}_i) : \gamma_\ell$	1.70	(2.08)
$g_{t-1}\mathscr{I}(\text{Small}_b) : \beta_s$	-0.59	(1.93)
$g_{t-1}\mathscr{I}(\text{Small}_b)\,\mathscr{I}(\text{Risky}_i) : \gamma_s$	-2.22^{**}	(1.08)
Impact of money growth on non-risky loans via large banks: α_g	-1.93	pv=0.33
Impact of money growth on *risky loans* via large banks: $\alpha_g + \gamma_\ell$	-0.23	pv=0.91
Impact of money growth on *risky loans* via small banks: $\alpha_g + \beta_s + \gamma_s$	-4.74^{**}	pv=0.02

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. The abbreviation "pv" stands for p-value.

Table 2.12: Estimated Results of Regression (8)

Explanatory variable	Coefficient	(Std. Err.)
$d_{t-1} : \alpha_d$	-5.31^{*}	(2.71)
$d_{t-1}\mathscr{I}\left(\text{Risky}_i\right) : \gamma_n$	5.08^{**}	(2.27)
$d_{t-1}\mathscr{I}\left(\text{Large}_b\right) : \beta_\ell$	2.80	(2.67)
$d_{t-1}\mathscr{I}\left(\text{Small}_b\right) : \beta_s$	2.73	(2.65)
$d_{t-1}\mathscr{I}\left(\text{Large}_b\right)\mathscr{I}\left(\text{Risky}_i\right) : \gamma_\ell$	-2.74^{*}	(1.68)
$d_{t-1}\mathscr{I}\left(\text{Small}_b\right)\mathscr{I}\left(\text{Risky}_i\right) : \gamma_s$	-5.01^{***}	(1.79)
of deposit growth on *risky loans* via NBTs: $\alpha_d + \gamma_n$	-0.23	pv=0.92
Impact of deposit growth on *risky loans* via large banks: $\alpha_d + \beta_\ell + \gamma_\ell$	-5.25^{**}	pv=0.03
Impact of deposit growth on *risky loans* via small banks: $\alpha_d + \beta_s + \gamma_s$	-7.59^{***}	pv=0.00

Note. * represents the 10% significance level, ** the 5% significance level, and *** the 1% significance level. NBTs stands for nonbank trustees. The abbreviation “pv” stands for p-value.

Table 2.13: Capital Adequacy Ratios, Excess Reserve Ratios, and LDRs Across Types of Banks and Samples

Description	Capital adequacy ratio		Excess reserve ratio		Loan-to-deport ratio	
	2007-2013	2010-2013	2007-2013	2010-2013	2007-2013	2010-2013
Large banks	12.60%	12.87%	1.95%	1.60%	64.03%	66.22%
Small banks	11.88%	12.30%	4.47%	3.17%	70.82%	67.89%
Overall	12.35%	12.65%	2.51%	2.01%	66.22%	66.80%

Note. Each reported ratio is weighted by bank assets. The calculation is based on the balance-sheet information of all commercial banks reported by Bankscope and WIND. Capital adequacy ratios and LDRs are from Bankscope and excess reserve ratios are from WIND.

Table 2.14: Correlation Between New Entrusted Loans ($\mathscr{S}$) Channeled by Banks snd Changes in ARI for Two Different Samples

Description	2007-2013 Sample		2010-2013 Sample	
	Small banks	Large banks	Small banks	Large banks
$Corr\,(\Delta\text{ARI}, \mathscr{S})$	.467*** (.001)	-.092 (.617)	.495*** (.007)	.025 (.929)
$Corr\left(\Delta\frac{\text{ARI}}{\text{ARI}+B}, \mathscr{S}\right)$	.386*** (.010)	-.121 (.509)	.330* (.087)	.008 (.978)

Note. The symbol "B" stands for traditional bank loans. The numbers in parentheses represent p-values.

Table 2.15: Correlation Between New *Risky* Entrusted Loans ($\mathscr{S}^r$) Channeled by Banks and Changes in ARI for Two Different Samples

Description	2007-2013 Sample		2010-2013 Sample	
	Small banks	Large banks	Small banks	Large banks
$Corr\,(\Delta\text{ARI}, \mathscr{S}^r)$	.433*** (.003)	-.058 (.754)	.501*** (.002)	.176 (.459)
$Corr\left(\Delta\frac{\text{ARI}}{\text{ARI}+B}, \mathscr{S}^r\right)$	.367** (.014)	-.088 (.631)	.362** (.033)	.187 (.430)

Note. The symbol "B" stands for traditional bank loans. The numbers in parentheses represent p-values.

Table 2.16: Balance Sheet at the Beginning of the Period

Assets	Liabilities
Cash ($C_t + (1-\delta)B_t$)	Deposits (D_t)
Loans ($q_t\delta B_t$)	Equity (E_t)

Table 2.17: Balance Sheet at the Beginning of the Period

Assets	Liabilities
Cash (C_t)	Deposits ($D_t - (1-\delta)B_t$)
Loans ($q_t\delta B_t$)	Equity (E_t)

Table 2.18: Balance Sheet after the Bank's Optimization

Assets	Liabilities
Cash $\left(\tilde{C}_t\right)$	Deposits
Risky assets	$\tilde{D}_t/R_t^D$
I_t^r	Equity
Safe loans $\tilde{B}_t$	$E_t - \text{DIV}_t +$ $(1-q_t^r)I_t^r + (1-q_t)\tilde{B}_t$

Table 2.19: Interest Rates of Risky and Non-risky Loans across Different Samples

Description	2007-2013	2010-2013
Bank loans	6.16%	6.00%
Non-risky entrusted loans	7.92%	7.71%
Risky entrusted loans	9.22%	9.05%

2.8 Appendix

2.8.1 Data Appendix

Given the large amount of data we have collected from various sources, we organize all the variables used in this paper and the corresponding data sources in the table below. Unless we indicate CEIC or Bankscope, all other data sources come from WIND.

Table 2.20: Variables and Data Sources

Data source A	Data source B
M2 growth	Names of borrowers
Growth in aggregate bank loans	Names of lenders
Growth in aggregate bank deposits	Names of trustees
Aggregate newly originated bank loans	Transactions announced by lenders
Total social financing bar stocks and bonds	Transactions announced by borrowers
Aggregate entrusted lending	Date of each transaction
Aggregate trust lending	Amount of each transacted entrusted loan
Bank acceptances	Interest rate of each transacted entrusted loan
GDP growth	Maturity of each transacted entrusted loan
Inflation	Affiliated loans
7-day CHIBOR rate	Borrower's industry
One-year base lending rate	
Data source C	**Data source D**
Loan-to-deposit ratio	Gross loan amount
Capital adequacy ratio	Total customer deposits
Excess reserves	Capital adequacy ratio
Total deposits	Bank equity
Amount of account receivable investment	Bank assets
Amount of bank lending	

Note: Data source A: CEIC. Data source B: announcements of entrusted loan transactions and annual reports of non-financial firms. Data source C: annual reports of listed commercial banks. Data source D: Bankscope (including non-listed banks). The variable "total deposits" from data source C is different from "total customer deposits" from data source D. Consistent with the PBC's requirements, "total deposits" is used to compute the reserve ratio while the loan-to-deposit ratio is computed as the ratio of "gross loan amount" and "total customer deposits". For the variable "capital adequacy ratio", we compare data sources C and D to make sure they match.

2.8.2 Regulation Timeline Appendix

The list of descriptions, below, organizes all the regulations either explicitly discussed in the paper or relevant to the discussion.

Regulations relevant to the discussions in the paper in chronological order (1995-2015)

LDR 5/10/1995. "*People's Republic of China Commercial Bank Law*" passed by the National People's Congress. The law specified the 75% LDR ceiling.

Entrusted Loans 8/1/1996. "*General Rules for Loans*" issued by the PBC. The regulation provided a definition of entrusted lending.

Entrusted Loans 4/5/2000. "*Notice on Issues Related to Practices of Commercial Banks In Entrusted Lending*" issued by the PBC. In the notice, the PBC changed the approval system to the registration system for entrusted loans.

Disclosure Requirements 12/1/2004. "*Stock Listing Rules of the Shanghai Stock Exchange*" issued by the Shanghai Stock Exchange. The rules required that a listed firm on Shanghai Stock Exchange must disclose every entrusted-loan transaction if the loan amount is larger than 10% of the firm's net assets, revenue, or profits.

Disclosure Requirements 12/1/2004. "*Stock Listing Rules of the Shenzhen Stock Exchange*" issued by the Shenzhen Stock Exchange. The rules required that a listed firms on Shenzhen Stock Exchange must disclose every entrusted-loan transaction if the loan amount is larger than 10% of the firm's net assets, revenue or profits.

Disclosure Requirements 10/27/2005. "*China Securities Law*" revised and passed by the Eighteenth Meeting of the Standing Committee of the Tenth National People's Congress. The law stated that listed firms must announce all major events which may have influenced their stock prices. This law applied to all listed firms that engaged in entrusted-loan transactions.

Risky Industry 5/28/2010. "*Notice on Financial Services to Further Support Energy Saving and Eliminate Backward-Production Capacity*" issued jointly by the PBC and CBRC. This regulation reinforced the 2006 notice issued by the State Council to make it operational to prohibit banks from originating new bank loans to the risky industry.

Risky Industry 6/12/2010. "*Reply to Number 001443 Proposal of the Third Session of the Eleventh National People's Congress*" issued by the CBRC. The reply stressed the need to continue curtailing expansion of traditional bank credits to the risky industry.

Risky Industry 8/8/2010. "*Number 111 Announcement on the Manufacturing Industry*" issued by China's Ministry of Industry and Information Technology. The announcement specifically classified the 18 overcapacity industries and reinforced the restriction of new bank credits to these industries.

Disclosure Requirements 8/18/2010. "*Memorandum of Information Disclosure for Small and Medium-Sized Enterprises*" issued by Shenzhen Stock Exchange. The memo required that a listed firm must disclose information of entrusted loans as long as its subsidiary firm was a lender of these loans, even if the company itself was not a direct lender.

LDR 1/1/2011. "*CARPALS Supervision System*" announced by the CBRC. The announcement provided 13 supervised indicators such as loan-to-deposit ratio and capital adequacy ratio and recommended that the PBC shall begin to monitor the LDR during the course of the year (quarterly) rather than at the end of the year.

Entrusted Loans 2/9/2011. "*Notice on Further Promoting Reforms and Development and on Strengthening Risk Management*" issued by the CBRC. Item 6 in this notice regulated how the businesses of "shadow banks" should operate and recognized a possibility of *regulatory arbitrage* by stating "when off-balance-sheet assets are brought into balance sheet, banks must calculate all relevant indicators such as leverage ratio and capital adequacy ratio."

Risky Industry 6/23/2011. "*Conference on the Bellwether Series*" held in China and organized by *The Economist*. An official from the CBRC who attended the conference stated the CBRC's requirement that commercial banks must continue to curtail bank loans to the real estate.

Disclosure Requirements 6/29/2011. "*Memorandum of Information Disclosure for Shenzhen Stock Exchange*" issued by Shenzhen Stock Exchange. The memo re-emphasized that a listed firm must disclose information of entrusted loans as long as its subsidiary firm was a lender of entrusted loans, even if the company itself was not a direct lender.

Disclosure Requirements 1/1/2012. "*Rules for Information Disclosure By Companies Offering Securities to the Public*" issued by China's Securities Regulatory Commission. The rules reinforce the requirement that every listed firm has the obligation to disclose *all entrusted-loan transactions*. This law is still in effect.

Risky Industry 7/5/2013. "*Guidelines for Financial Support of Economic Structure Adjustments and for Transformation and Upgrade of the Insurance Industry*" issued by the State Council. These guidelines reiterated the law that prohibited banks from providing new credits to the risky industry.

Shadow Banking 12/10/2013. "*Notice on Issues of Tightening Regulations on Shadow Banking*" issued by the State Council. The notice mentioned possible regulatory-arbitrage problems associated with shadow banking, suggested the potential systemic risk caused by shadow banking, and tightened regulations on the shadow banking system including entrusted loans.

Nonstandard Assets 4/29/2014. "*Official Meeting on Financial and Economic Analyses*" held by the CBRC. The meeting identified "nonstandard assets" as a threat to the health of the financial system and specifically outlining steps in containing the riskiness of entrusted lending and entrusted rights in the banking system.

Last-Minute Rush 9/12/2014. "*Number 236 Notice on Strengthening Commercial Banks' Deposit Stability Management*" issued jointly by CBRC, the Ministry of Finance, and the PBC. The notice identified last-minute actions taken by banks to pay high prices to artificially increase temporary deposits in order to recoup deposit shortfalls when the PBC's deposit-monitoring time was near. While the notice applied to all banks, it effectively banned the practice of small banks in acquiring additional deposits through the WMP channel, by offering higher deposit rates, or through other high-cost means.

Entrusted Loans 1/16/2015. "*Draft for Management Rules on Commercial Banks' Entrusted Loans: Open for Public Opinions*" issued by the CBRC. The draft reinforced the earlier regulations that commercial banks were prohibited from taking on credit risks when facilitating entrusted loans.

LDR Ceiling Removal 6/24/2015. "*People's Republic of China Commercial Bank*

Law Amendment (Draft)" proposed by the State Council on that day and approved by the Standing Committee of the National People's Congress on 20 August 2015. It removed the LDR ceiling and thus officially ended this regulation enacted in 1995.

Deposit Rate Ceiling Removal 10/24/2015. "*Notice on the Removal of Deposit Rate Ceiling of Commercial Banks*" issued by the PBC. The notice removed the ceiling of bank deposit rates.

2.8.3 Technical Appendix: Proofs of Propositions 1-3

Proof of Proposition 1

The proof for Proposition 1 follows from the fact that E is a sufficient statistics for the bank's problem. In other words, once E is determined, the bank's optimal decision does not depend on the sources from which the equity E is accumulated.

Proof of Proposition 2

Homogeneity: We use the conjecture-verify approach to this complicated problem. We conjecture the form of the value function as

$$V(E;z) = v(z)E^{1-\gamma}.$$

Because

$$E' = e'(\omega, \varepsilon; z', z)E,$$

the optimization problem (2.32) can be rewritten as

$$\begin{aligned} V(E;z) &= \max U(\operatorname{div} E) + \beta E_{M,\omega,\varepsilon}\left[v(z')\ \left(e'(\omega,\varepsilon;z',z)E\right)^{1-\gamma} \mid z\right] \\ &= E^{1-\gamma}\left\{\max U(\operatorname{div}) + \beta E_{M,\omega,\varepsilon}\left[v(z')\ \left(e'(\omega,\varepsilon;z',z)\right)^{1-\gamma} \mid z\right]\right\} \end{aligned}$$

subject to (2.36), (2.37), and (2.38). Let $\tilde{v}(z)$ be the solution of

$$\tilde{v}(z) = \max U(\operatorname{div}) + \beta E_{M,\omega,\varepsilon}\left[\tilde{v}(z')\ \left(e'(\omega,\varepsilon;z',z)\right)^{1-\gamma} \mid z\right] \tag{2.50}$$

subject to (2.36), (2.37) and (2.38). Hence $v(z) = \tilde{v}(z)$, which verifies the guess to our Bellman equation

$$V(E;z) = v(z)E^{1-\gamma}.$$

From (2.45) we have

$$\left(e'(\omega,\varepsilon;z',z)\right)^{1-\gamma} = (1-\text{div})^{1-\gamma}\left(R^E(\omega,\varepsilon;z',z)\right)^{1-\gamma}$$

so that

$$E_{\omega,\varepsilon}\left[\left(e'(\omega,\varepsilon;z',z)\right)^{1-\gamma}\right] = (1-\text{div})^{1-\gamma}E_{\omega,\varepsilon}\left[\left(R^E(\omega,\varepsilon;z',z)\right)^{1-\gamma}\right]. \tag{2.51}$$

Since the utility is power utility, the certainty equivalence of $E_{\omega,\varepsilon}\left[\left(R^E(\omega,\varepsilon;z',z)\right)^{1-\gamma}\right]$, denoted as $\Omega(z',z)$, follows as

$$\Omega(z',z) = \max_{\{w_c,w_i,w_b,w_d\}}\left\{E_{\omega,\varepsilon}\left[\left(R^E(\omega,\varepsilon;z',z)\right)^{1-\gamma}\right]\right\}^{\frac{1}{1-\gamma}} \tag{2.52}$$

$$= \max_{\{w_c,w_i,w_b,w_d\}}\left\{E_{\omega,\varepsilon}\left[\left(w_c + R^I w_i + R^B w_b - R^D w_d - R^x\right)^{1-\gamma}\right]\right\}^{\frac{1}{1-\gamma}} \tag{2.53}$$

subject to (2.41) and (2.42). Substituting (2.51) into (2.50) and using the definition of $\Omega(z',z)$ in (2.53), we obtain (2.44).

Proof of Proposition 3

As p^ω increases, we first establish that the share of risky assets in total assets, $\frac{q^r I^r}{q^r I^r + qB'}$ or $\frac{q^r I^r}{q^r I^r + q\widetilde{B}}$, increases; we then prove that the volume of risky assets, $q^r I^r$, increases as well.

Combining (2.41) and (2.42) and substituting them into (2.53) transforms the optimization problem to

$$\Omega(z',z) = \max_{\{w_c,w_i,w_b,w_d\}}\Big\{E_{\omega,\varepsilon}\Big[\Big(R^B - (R^B-1)w_c + (R^I - R^B)w_i$$
$$-(R^B - R^D)w_d - R^x(w_b,w_d;\omega)\Big)^{1-\gamma}\Big]\Big\}^{\frac{1}{1-\gamma}} \tag{2.54}$$

subject to $w_d \leq \kappa$ (with the Lagrangian multiplier ϕ_d) and $w_c \geq 0$ (with the Lagrangian multiplier ϕ_c). The first order condition with respect to w_c gives

$$\phi_c - (R^B - 1)E_{\omega,\varepsilon}(R^E)^{-\gamma}\left[E_{\omega,\varepsilon}(R^E)^{1-\gamma}\right]^{\gamma/(1-\gamma)} = 0.$$

It follows from $R^B > 1$ that $\phi_c > 0$, which implies that $w_c = 0$.

Substituting $w_c = 0$ and $w_i = 1 - w_b + w_d$ into (2.54) reduces the optimization problem to

$$\begin{aligned}
&\Omega(z', z) \\
&\quad = \max_{\{w_b, w_d\}} \left\{ E_{\omega,\varepsilon}\left[\left(R^I + (R^B - R^I)w_b + (R^I - R^D)w_d - R^x(w_b, w_d; \omega)\right)^{1-\gamma}\right]\right\}^{\frac{1}{1-\gamma}}
\end{aligned} \tag{2.55}$$

subject to $w_d \leq \kappa$ and $\phi_d(\kappa - w_d) = 0$. The first order condition with respect to w_b gives

$$\begin{aligned}
&\left[E_{\omega,\varepsilon}(R^E)^{1-\gamma}\right]^{\gamma/(1-\gamma)} E_{\omega,\varepsilon}(R^E)^{-\gamma} E_\varepsilon\left[R^B - R^I\right] \\
&\qquad - \left[E_{\omega,\varepsilon}(R^E)^{1-\gamma}\right]^{\gamma/(1-\gamma)} E_{\omega,\varepsilon}\left[(R^E)^{-\gamma} R_b^x(w_b, w_d; \omega)\right] = 0,
\end{aligned}$$

where

$$R_b^x(w_b, w_d; \omega) = \frac{\partial R^x(w_b, w_d; \omega)}{\partial w_b}.$$

Noting from (2.46) that R^E depends on both ω and ε, we simplify the above expression as

$$R^B E_\varepsilon\left[E_\omega(R^E)^{-\gamma}\right] - E_\varepsilon\left[R^I E_\omega(R^E)^{-\gamma}\right] = E_{\omega,\varepsilon}\left[(R^E)^{-\gamma} R_b^x(w_b, w_d; \omega)\right]$$

$\Longleftrightarrow$

$$R^B - \frac{E_\varepsilon\left[R^I E_\omega(R^E)^{-\gamma}\right]}{E_\varepsilon\left[E_\omega(R^E)^{-\gamma}\right]} = \frac{E_{\omega,\varepsilon}\left[(R^E)^{-\gamma} R_b^x(w_b, w_d; \omega)\right]}{E_\varepsilon\left[E_\omega(R^E)^{-\gamma}\right]},$$

which leads to the asset-pricing condition between safe loans and risky investment:

$$R^B - \underbrace{E_\omega\left[R_b^x(w_b, w_d; \omega)\right]}_{\text{expected regulation cost}} = E_\varepsilon(R^I) - \underbrace{\left[-\frac{\mathrm{Cov}_\varepsilon\left(R^I, E_\omega(R^E)^{-\gamma}\right)}{E_\varepsilon\left[E_\omega(R^E)^{-\gamma}\right]}\right]}_{\text{default risk premium}}.$$

The left-hand-side term represents the *effective* return to safe loans, expressed as the bank lending rate minus the expected regulation cost. The right-hand-side term is the expected return to risky investment, adjusted for the risk premium of default. Note that the risk premium is positive. The expected regulation cost is the expected marginal cost of meeting the LDR ceiling. Indeed, it is straightforward to show that this regulation cost is

$$E_\omega\left[R_b^x(w_b, w_d; \omega)\right] = \underbrace{\mathrm{Prob}\left(\theta\omega \geq \theta - \tilde{B}/\tilde{D}\right)}_{\text{regulation risk}} r^b. \tag{2.56}$$

By defining $L = \frac{w_b}{w_d}$ as the LDR, we can rewrite the bank's portfolio choice problem (2.55) as

$$\begin{aligned} & \Omega\left(z', z\right) \\ = \; & \max_{L, w_d}\left\{E_{\omega,\varepsilon}\left[R^I + w_d\left[\left(R^I - R^D\right) - \left(R^I - R^B\right)L - R^x\left(L, 1; \omega\right)\right]\right]\right\}^{\frac{1}{1-\gamma}} \end{aligned}$$

subject to $w_d \leq \kappa$. The first order condition with respect to L is

$$R^B - \underbrace{E_\omega\left[R_L^x\left(L, 1; \omega\right)\right]}_{\text{expected liquidity cost}} = E_\varepsilon\left(R^I\right) - \underbrace{\left[-\frac{Cov_\varepsilon\left(R^I, E_\omega\left(R^E\right)^{-\gamma}\right)}{E_\varepsilon\left[E_\omega\left(R^E\right)^{-\gamma}\right]}\right]}_{\text{default risk premium}}, \tag{2.57}$$

where

$$R_L^x\left(L, 1; \omega\right) = \frac{\partial R^x\left(L, 1; \omega\right)}{\partial L}.$$

This asset-pricing equation with respect to L is an alternative expression of the previous asset-pricing equation with respect to w_b (i.e., equation (2.47)). As one can see from below, this alternative expression makes our proof more transparent.

By definition,

$$\frac{q^r I^r}{q^r I^r + q\widetilde{B}} = \frac{w_i}{w_i + w_b} = \frac{1}{1 + w_b/w_i}.$$

To prove that the share of risky assets increases with p^ω is equivalent to prove that $\frac{\partial w_b/w_i}{\partial p^\omega} < 0$. When p^ω increases, $E_\omega\left[R_L^x\left(L, 1; \omega\right)\right]$ will increase. It follows from (2.57) that the effective return to safe loans will decline *relative to* the effective return to risky investment. Hence, w_b/w_i falls, implying that $\frac{q^r I^r}{q^r I^r + q\widetilde{B}}$ increases.

We now prove that $\frac{\partial q^r I^r}{\partial p^\omega} > 0$. We first establish the following lemma.

Lemma 1. With the low deposit rate such that

$$R^D < R^B - r^b p^\omega, \tag{2.58}$$

the credit constraint (2.26) or $w_d \leq \kappa$ is binding.

Proof: When $\omega = 0$, there is no need to acquire additional deposits to meet the LDR ceiling. When $\omega = 1$, however, the bank always needs to acquire additional deposits in order to meet the LDR requirement $L \leq \theta$. Accordingly,

$$E_\omega\left[R^x\left(L, 1; \omega\right)\right] = r^b p^\omega L \tag{2.59}$$

and

$$E_\omega\left[R_L^x\left(L, 1; \omega\right)\right] = r^b p^\omega. \tag{2.60}$$

Define the leverage return as

$$R^L = \left(R^I - R^D\right) - \left(R^I - R^B\right) L - R^x\left(L, 1; \omega\right).$$

We have

$$E_{\omega,\varepsilon}\left[R^{L}\left(L;\omega,\varepsilon\right)\right]=E_{\varepsilon}\left[\left(1-L\right)\left(R^{I}-R^{D}\right)+L\left(R^{B}-R^{D}\right)\right]-E_{\omega}\left[R^{x}\left(L,1;\omega\right)\right] \tag{2.61}$$

The first order condition for w_d is

$$E_{\omega,\varepsilon}\left[R^{L}\left(L;\omega,\varepsilon\right)\right]-\left[-\frac{Cov_{\varepsilon}\left(E_{\omega}\left(R^{E}\right)^{-\gamma},R^{L}\right)}{E_{\varepsilon}\left[E_{\omega}\left(R^{E}\right)^{-\gamma}\right]}\right]=\widetilde{\phi}^{d} \tag{2.62}$$

where $\widetilde{\phi}^{d}=\frac{\phi^{d}}{\left[E_{\omega,\varepsilon}(R^{E})^{1-\gamma}\right]^{\frac{\gamma}{1-\gamma}}E_{\omega}\left[E_{\varepsilon}(R^{E})^{-\gamma}\right]}$. The left-hand-side term is the effective expected return to leverage, adjusted for the default risk premium and the expected regulation cost.

To prove the credit constraint is binding, it is equivalent to show that the effective expected return to leverage is positive. That is, we need to show

$$E_{\omega,\varepsilon}\left[R^{L}\left(L;\omega,\varepsilon\right)\right]-\left[-\frac{Cov_{\varepsilon}\left(E_{\omega}\left(R^{E}\right)^{-\gamma},R^{L}\right)}{E_{\varepsilon}\left[E_{\omega}\left(R^{E}\right)^{-\gamma}\right]}\right]>0,$$

which implies that $\widetilde{\phi}^{d}>0$ or $\phi^{d}>0$.

According to the definition of R^L,

$$\frac{Cov_{\varepsilon}\left(E_{\omega}\left(R^{E}\right)^{-\gamma},R^{L}\right)}{E_{\varepsilon}\left[E_{\omega}\left(R^{E}\right)^{-\gamma}\right]}=\frac{\left(1-L\right)Cov_{\varepsilon}\left(E_{\omega}\left(R^{E}\right)^{-\gamma},R^{I}\right)}{E_{\varepsilon}\left[E_{\omega}\left(R^{E}\right)^{-\gamma}\right]}. \tag{2.63}$$

Combining equation (2.59) with equation (2.60) leads to

$$E_{\omega}\left[R^{x}\left(L,1;\omega\right)\right]=LE_{\omega}\left[R_{L}^{x}\left(L,1;\omega\right)\right]. \tag{2.64}$$

Substituting both (2.63) and (2.64) into the left side of (2.62) and reordering, we have

$$
\begin{aligned}
& E_{\omega,\varepsilon}\left[R^L(L;\omega,\varepsilon)\right] - \left[-\frac{Cov_\varepsilon\left(E_\omega\left(R^E\right)^{-\gamma}, R^L\right)}{E_\varepsilon\left[E_\omega\left(R^E\right)^{-\gamma}\right]}\right] \\
= \; & (1-L)\left\{E_\varepsilon\left(R^I\right) - \left[\frac{Cov_\varepsilon\left(E_\omega\left(R^E\right)^{-\gamma}, R^I\right)}{E_\varepsilon\left[E_\omega\left(R^E\right)^{-\gamma}\right]}\right]\right\} + L\left\{R^B - E_\omega\left[R_L^x(L,1;\omega)\right]\right\} - R^D \\
= \; & R^B - E_\omega\left[R_L^x(L,1;\omega)\right] - R^D,
\end{aligned}
$$

where the second equality comes from the asset-pricing condition (2.57) . Given (2.60) and (2.58), we have

$$
E_{\omega,\varepsilon}\left[R^L(L;\omega,\varepsilon)\right] - \left[-\frac{Cov_\varepsilon\left(E_\omega\left(R^E\right)^{-\gamma}, R^L\right)}{E_\varepsilon\left[E_\omega\left(R^E\right)^{-\gamma}\right]}\right] > 0.
$$

Hence, $\widetilde{\phi}^d > 0$ or $\phi^d > 0$.

We are ready to prove $\partial\left(q^r I^r\right)/\partial p^\omega > 0$. Because $q^r I^r = w_i\left(1 - div\right)E$, it is sufficient to prove that $\partial w_i/\partial p^\omega > 0$ and $\partial \mathrm{div}/\partial p^\omega \le 0$. Since $w_i + w_b = 1 + w_d$, we have $\frac{w_i}{w_i+w_b} = \frac{w_i}{1+w_d} = \frac{w_i}{1+\kappa}$. Therefore, $\partial\frac{q^r I^r}{q^r I^r + q\widetilde{B}}/\partial p^\omega > 0$ gives $\partial w_i/\partial p^\omega > 0$.

We now need to prove $\partial \mathrm{div}/\partial p^\omega \le 0$. The Euler equation associated with problem (2.44) can be written as

$$
\begin{aligned}
\mathrm{div}^{-\gamma} &= \beta(1-\gamma)(1-\mathrm{div})^{-\gamma} E_M\left[E_{\omega\varepsilon}\left(R^E\right)^{1-\gamma} v(z') \mid z\right] \\
&= \beta(1-\gamma)(1-\mathrm{div})^{-\gamma} E_M\left[v(z') \mid z\right] \\
&\quad \left[p^\omega E_\varepsilon\left(R^E\left(\omega^l\right)\right)^{1-\gamma} + (1-p^\omega) E_\varepsilon\left(R^E\left(\omega^h\right)\right)^{1-\gamma}\right] \qquad (2.65)
\end{aligned}
$$

Equation (2.65) expresses div as an implicit function of p^ω. Taking partial derivative of div with respect to p^{ω} and reorganizing the terms, we obtain

$$\frac{\partial \text{div}}{\partial p^{\omega}} = \frac{E_{\varepsilon}\left[\left(R^{E}\left(\omega^{l}\right)\right)^{1-\gamma} - \left(R^{E}\left(\omega^{h}\right)\right)^{1-\gamma}\right] \beta\left(1-\gamma\right) E_{M}\left[v\left(z'\right) \mid z\right]\left(1-\text{div}\right)^{-\gamma-1}}{-\gamma \text{div}^{-\gamma-1} - \beta\gamma\left(1-\gamma\right) E_{M}\left[v\left(z'\right) \mid z\right]\left(1-\text{div}\right)^{-\gamma-1} E_{\omega\varepsilon}\left[\left(R^{E}\right)^{1-\gamma}\right]}. \tag{2.66}$$

The denominator of (2.66) is always negative, thanks to the concavity of the bank's utility function.[30] For the numerator, whether it is positive or not depends on $\left(R^{E}\left(\omega^{l}\right)\right)^{1-\gamma} - \left(R^{E}\left(\omega^{h}\right)\right)^{1-\gamma} |_{\varepsilon} \gtrless 0$. Since $R^{E}\left(\omega^{l}\right) - R^{E}\left(\omega^{h}\right) |_{\varepsilon} < 0$ and given $\gamma \geq 1$, we have

$$\left(R^{E}\left(\omega^{l}\right)\right)^{1-\gamma} - \left(R^{E}\left(\omega^{h}\right)\right)^{1-\gamma} |_{\varepsilon} \geq 0.$$

Therefore, $\partial \text{div}/\partial p^{\omega} \leq 0$. With $\partial w_i/\partial p^{\omega} > 0$, we have $\partial\left(q^{r} I^{r}\right)/\partial p^{\omega} > 0$.■

[30]Note that $\left(1-\gamma\right) E_{M}\left[v\left(z'\right) \mid z\right] > 0$.

Part III

Measuring Mutual Fund Skill With Active Alphas

(joint with Jeong Ho (John) Kim)

Abstract

This paper examines whether high beta mutual funds are associated with high alphas or low alphas. Similar to the findings for various assets in Frazzini and Pedersen (2014), we find some evidence that high beta mutual funds have low standard alphas. However, when we explore the relationship between mutual fund beta and active alpha, a measure that we define as the difference between a mutual fund's standard alpha and the matching stock alpha, we find that the active alphas monotonically increase in beta. After adjusting mutual fund returns by a passive stock benchmark, the high beta mutual funds appear to display more skills.

JEL: C12,C15,G11

Key Words: Mutual Fund, Factor Model, Performance Evaluation

3.1 Introduction

We look at the impact of beta exposure on mutual fund performance. Similar to the findings in Frazzini and Pedersen (2014), we document that high market beta exposure is associated with low mutual fund standard alpha. However, the standard alphas do not truly measure the skill of managers because the mutual fund stock holdings have different alpha levels. We construct an active alpha measure that adjusts the standard alpha according to a passive benchmark. The benchmark is an equal weighted portfolio of stocks that match the mutual fund holding based market beta. Next, we explore the relationship between mutual fund betas and active alphas. We document that the active alphas almost monotonically increase in beta. After adjusting mutual fund returns by a passive stock benchmark, the high beta mutual funds appear to have more skills.

Our results contribute to the literature on risk and return tradeoff. Frazzini and Pedersen (2014) document that high beta assets are associated with low risk adjusted return. Hong and Sraer (2016) find that stock expected returns actually decrease with beta during high aggregate disagreement periods . Our paper finds similar results with respect to mutual fund returns, but introduces an additional measure. This paper is also related to the recent work on mutual fund performance evaluation. Daniel et al. (1997) develop a new mutual fund performance measure that uses benchmarks based on the characteristics of stocks held by the mutual funds. Busse et al. (2017) propose an approach for estimating mutual fund performance that controls for both factor model market beta and stock characteristics. Hoberg, Kumar, and Prabhala (2016) proposed a customized peer alpha by considering mutual funds performance relative to the alternate active fund with the same risk profile . Our paper is different from these papers because we use a passive stock benchmark constructed by matching beta exposures to evaluate mutual fund performance.

The rest of the paper is organized as follows. Section 3.2 details the data source and variable construction. Section 3.3 discuss empirical specisication. Section 3.4 presents the results on the standard alphas and active alphas. Section 3.5 conducts robustness check. Section 3.6 concludes the paper.

3.2 Data

3.2.1 Data Description

The data on mutual funds are from several sources: Morningstar Direct, CRSP, and Thomson Reuters Mutual Fund Holdings database. The sample contains 2,922 actively managed domestic equity-only mutual funds from the United States between 1980 and 2014. Our first data source is the Morningstar Direct database, which covers U.S. open-end mutual funds and provides information about fund names, returns, assets, inception dates, expense ratios, turnover ratios, investment strategies classified into Morningstar Categories, and other fund characteristics. Pastor, Stambaugh, and Taylor (2015) create a CRSP and Morningstar cross-validated dataset of actively managed US equity mutual funds, building on the work of Berk and van Binsbergen (2014). We follow closely the Data Appendix to Pastor, Stambaugh, and Taylor (2015)[1] in merging Morningstar and CRSP database. We exclude bond funds, money market funds, international funds, funds of funds, industry funds, real estate funds, target retirement funds, non-equity funds, and index funds. Following Elton et al. (2001), Chen et al. (2004), Yan (2008), and Pastor et al. (2015), we exclude funds with less than $15 million in TNA.

[1] http://faculty.chicagobooth.edu/lubos.pastor/research/Data_Appendix_Aug_2013_V3.pdf.

The Thomson Reuters Mutual Fund Holdings database provides quarterly mutual fund portfolio holding information. We merge our sample of domestic equity funds and Thomson Reuters Mutual Funds Holdings database using the MFLINKS tables available via WRDS. The SEC's mandatory reporting frequency of mutual fund holdings is quarterly prior to 1985, semi-annual between 1985 and May 2004, and quarterly again afterwards. For funds that do not report quarterly, we extrapolate the previous quarter holdings to the current quarter. This is done for at most one quarter to avoid excessively stale data. We further assume that the mutual fund holding does not change for each month within the same quarter. In addition, Funds report holdings at the end of their fiscal quarter, which may not always be the end of a calendar quarter. In order to facilitate cross-sectional comparison, if the date of the reported holdings is not at a calendar quarter end, we assume that the holdings remain valid at the end of that calendar quarter, with adjustment for stock splits using the CRSP share adjustment factor.

We obtain monthly data for the size, value, momentum, and market portfolios for the period of 1980 to 2014 from Kenneth French's data library.

3.2.2 Variable Construction

Mutual Fund Return:

Following Daniel et al. (1997), we use the hypothetical fund returns as an estimate of the gross returns of the fund. We calculate the hypothetical monthly returns that would be generated by buying the number of shares of each CRSP listed stock held by the fund on the first day of each quarter and holding the portfolio until the first day of the following quarter. To mitigate the impact of outliers on our estimates, we winsorize the gross return at the 0.5% level.

Standard Fund Performance:

In accord with the mutual fund performance measurement literature, we construct four standard fund performance measures to evaluate funds' risk-adjusted performance. We adjust funds' returns using the Capital Asset Pricing Model (CAPM), the three-factor model, the Carhart (1997) four-factor model, and the five-factor model including the traded liquidity factor by Pastor and Stambaugh (2003). For the main result in Section 0.4, we estimate mutual fund standard alpha as the intercept in a regression of mutual fund monthly excess returns over the whole sample period. As a robustness check, we also estimate alphas over a 24-month estimation period, rolling this window one month at a time. The rolling regression results are shown in Section 3.5.1.

CAPM Alpha: We first estimate the standard alpha as the intercept of regression 3.1 over the whole sample period.

$$R_{it} - R_{ft} = a_i + \beta_{it}(R_{Mt} - R_{ft}) + \varepsilon_{it} \tag{3.1}$$

where R_{it} is the gross return for mutual fund i in month t, R_{ft} is the risk-free rate in month t, and R_{Mt} is the return on the market portfolio in month t. As a robustness check, we also estimate regression 3.1 over a 24-month estimation period, rolling this window a month at a time.

Three-Factor Alpha: We follow a similar methodology in calculating the three-factor alpha. We estimate regression 3.2 over the whole sample. In addition, we estimate regression 3.2 using a 24-month rolling window.

$$R_{it} - R_{ft} = a_i + \beta_{it}^{MKT}(R_{Mt} - R_{ft}) + \beta_{it}^{SMB} SMB_t + \beta_{it}^{HML} HML_t + \varepsilon_{it} \tag{3.2}$$

where SMB_t and HML_t are the size and value factors as in Fama and French (1993).

Four-Factor Alpha: Based on the three-factor model, we add the momentum factor as in Carhart (1997). We use the same method to calculate the time invariant

Four-Factor Alpha and rolling window Four-Factor Alpha.

$$R_{it} - R_{ft} = a_i + \beta_{it}^{MKT}(R_{Mt} - R_{ft}) + \beta_{it}^{SMB} SMB_t + \beta_{it}^{HML} HML_t + \beta_{it}^{MOM} MOM_t + \varepsilon_{it} \tag{3.3}$$

where MOM_t is Carhart's (1997) momentum factor.

Five-Factor Alpha: We include the traded liquidity factor by Pastor and Stambaugh (2003) when estimating the following regression:

$$R_{it} - R_{ft} = a_i + \beta_{it}^{MKT}(R_{Mt} - R_{ft}) + \beta_{it}^{SMB} SMB_t + \beta_{it}^{HML} HML_t + \beta_{it}^{MOM} MOM_t + \beta_{it}^{LIQ} LIQ_t + \varepsilon_{it} \tag{3.4}$$

where LIQ_t is traded liquidity factor by Pastor and Stambaugh (2003).

Stock Betas:

At the end of each calendar month, we use previous 12-month daily stock return data to estimate the factor loadings for stocks. Following Frazzini and Pedersen (2014), we estimate volatilities and correlations separately to account for the fact that correlations move more slowly than volatilities. Our estimated market beta for stock i is given by

$$\hat{\beta}_i^{MKT} = \hat{\rho}_{iMKT} \frac{\hat{\sigma}_i}{\hat{\sigma}_{MKT}}$$

where $\hat{\sigma}_i$and $\hat{\sigma}_{MKT}$ are the estimated volatilities for the stock and the market, and $\hat{\rho}$ is their correlation. We use one-day log returns to estimate volatilities and overlapping three-day log returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} ln(1 + r_{t+k}^{i})$, for correlation to control for non-synchronous trading.

Mutual Fund Holding Based Betas:

After obtaining estimates of factor loadings for each stock i during each month t, we weight each stock-level factor loading according to its dollar weight in the most recent fund portfolio holdings to calculate the monthly mutual fund holding based factor loadings. The holding based factor loadings for fund j during month t could be expressed as:

$$Fund\beta_j = \sum_{i=1}^{N_j} w_{i,j,t}\beta_{it}$$

where N_j is the number of stocks held by fund j, and $w_{i,j,t}$ is the weight of stock i in month t.

In Table 1, we sort funds by one-month lagged mutual fund holding based market beta into quintiles and report the summary statistics for the five portfolios. The sample period is 1980m4-2014m12. The unit of observation is fund-month. In the second column of Table 1, we show the average of holding based beta for each portfolio. To calculate the holding based market beta, we weight each stock-level factor loading according to its dollar weight in the most recent fund portfolio holdings. Figure 1 plots the histogram of mutual fund holding based betas for all funds in our sample.

The third column of Table 1 reports the mutual fund gross returns. Mutual fund gross returns are calculated by buying the number of shares of each CRSP listed stock held by the fund on the first day of each quarter and holding the portfolio until the first day of the following quarter. We winsorize gross returns at the 0.5th and 99.5th percentiles. We report the returns of passive benchmark portfolios for each quintile of mutual funds in the fourth column of Table 1. The benchmark is an equal weighted portfolio of stocks that satisfies two criteria: 1) the stocks are held by at least one mutual fund in a given month, and 2) the stocks match the mutual fund holding based market beta. In the bottom Panel of Figure 2 , we plot the histogram of all the betas for stocks that appear in the benchmark. The fifth column reports mutual fund active return, which is the benchmark adjusted return formed by taking the difference of the gross returns in column 3 and the benchmark returns in column

4.

3.3 Empirical Specification - Active Alpha

Each month, we sort funds into quintiles based on one-month lagged holding based betas. For each mutual fund portfolio, we consider two types of alphas: the standard alpha and the active alpha. The standard alpha is the intercept in a regression of mutual fund portfolios' monthly excess return over the whole sample period. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. Following Daniel et.al (1997), we use the hypothetical fund returns as an estimate of the gross returns of the fund. We calculate the hypothetical monthly returns that would be generated by buying the number of shares of each CRSP listed stock held by the fund on the first day of each quarter and holding the portfolio until the first day of the following quarter.

We construct mutual fund active alphas in three steps. In the first step, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is an equal weighted portfolio of stocks that satisfies two criteria. The first criteria is that the stocks are held by at least one mutual fund in a given month. It is possible that a mutual fund would not be able to hold some stocks because of liquidity concerns. To address this concern, we restrict our stock universe to the stocks reported in the Thomson Reuters Mutual Fund Holding database.

The second criteria is that the stocks match the mutual fund holding based market beta. For example, the mutual fund holding based market beta range is 0.8-1 for the bottom quintile of market betas univariate sort mutual funds in 2014 m1. For that month, we will form a stock portfolio by including all the stocks which are held by at least one mutual fund and have a market beta between 0.8 to 1. If stocks do not fall in the mutual fund portfolios' range of holding based beta in certain month, those stocks will not be included in the matching stock portfolios.

In the second step, we subtract the returns of a passive benchmark stock portfolio from the mutual fund gross returns to calculate the mutual fund benchmark adjusted returns. In the final step, mutual fund active alpha is the intercept in a regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor.The active alpha evaluates mutual fund performance controlling for the mutual fund holding's beta exposure.

3.4 Results

In this section, we study how holding based market betas impact mutual fund standard and active alphas. In Section 3.4.1 and 3.4.2, we examine the impact of beta on all actively managed mutual funds. Section 3.4.3 further analyzes the impact of holding based market betas on various styles of mutual funds.

3.4.1 Relation between Standard Alphas and Holding Based Market Betas

We first explore whether various measures of mutual fund standard alphas increase or decrease with holding based market betas. Each calendar month, we sort funds by their one-month lagged holding based market betas into quintiles to obtain 5 equal weighted mutual fund portfolios. Mutual fund standard alpha is the intercept in a regression of mutual fund monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. Following Daniel et al. (1997), we use the hypothetical fund returns as an estimate of the gross returns of the fund. We calculate the hypothetical monthly returns that would be generated by buying the number of shares of each CRSP listed stock held by the fund on the first day of each quarter and holding the portfolio until the first day of the following quarter. Frazzini and Pedersen (2014) finds that standard alpha measures decrease with beta exposures for many financial assets. We would expect standard alphas to monotonically decline with mutual fund holding based betas.

Panel A of Table 3.2 reports statistics for standard alphas of quintile portfolios obtained from univariate sorts based on the one-month lagged mutual fund holding based market beta. The standard alphas decline almost monotonically from low holding based market beta to high holding based market beta mutual fund portfolios. The pattern persists when the standard alphas are estimated relative to a CAPM, three-, four-and five-factor models. The bottom row of the Panel A of Table3.2 shows the standard alphas of a portfolio that is long in the high beta mutual fund portfolio (B5) and short in the low beta mutual fund portfolio (B1). The result indicates that the CAPM standard alpha difference between the top beta quintile and bottom beta quintile is statistically significant at the one percent level. The magnitude of the difference is economically large. The standard alpha for the top quintile of the holding based market beta portfolio has an annualized CAPM alpha that is 4.17% (t-stat.= 2.41) higher than the bottom quintile of the holding based market beta portfolio. After adjusting for additional risk factors, the three-, four-, and five-factor standard alphas are not statistically significant.

Next, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is an equal weighted portfolio of stocks which satisfies two criteria: 1) The stocks are held by at least one mutual fund in the given month; 2) The stocks' betas match the mutual fund holding based market beta. Panel B of Table 3.2 reports the standard alphas for the passive benchmark stock portfolios, which are formed based on the beta range of the mutual fund portfolio. Standard alphas of the passive benchmark stock portfolio also monotonically decline in beta.

3.4.2 Relation between Active Alphas and Holding Based Market Betas

Mutual fund active alpha is the intercept in a regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. To calculate mutual fund benchmark adjusted return, we subtract the returns of a matching passive benchmark stock portfolio from mutual fund gross returns. The matching principle is discussed in Section 3.3.

Table 3.3 shows the mutual fund active alphas of quintile portfolios obtained from univariate sorts of one-month lagged mutual fund holding based market beta. The active alphas increase almost monotonically from low holding based market beta to high holding based market beta mutual fund portfolios. The patterns of the active alphas are opposite to those of the standard alphas. The bottom row of the Table 3.3 shows the active alpha of a portfolio that is long in the high beta mutual fund portfolio (B5) and short in the low beta mutual fund portfolio (B1). The difference in active alphas between the top beta quintile and bottom beta quintile is statistically significant for all factor models. Also, the magnitude of the difference is economically large. The active alpha for the top quintile of holding based market beta portfolios has an annualized CAPM alpha that is 4.86% (t-stat.= 3.05) higher than the bottom quintile of holding based market beta portfolios. The active alpha results suggest that high beta mutual funds display more skills after adjusting for the passive exposure to stock betas. The standard alpha measure attributes some of the passive beta exposure from stocks to managerial skills.

3.4.3 Standard Alphas and Active Alphas for Various Style of Mutual Fund

In this Section, we examine weather standard alphas decrease with holding based market beta for different styles of mutual fund. We consider nine Morningstar style categories. The Morningstar style box is a nine-square grid that classifies a fund's investment style based on its holding. The style box classifies funds by whether they own large-, mid-, or small-capitalization stocks, and by whether those stocks have growth or value characteristics or land somewhere in between. We explore the fund performance for these nine Morningstar categories.

We implement the standard alpha and the active alpha calculation as describe in Section 3.3 for mutual funds in each Morningstar categories. Table 3.4 reports the standard alphas of quintile portfolios obtained from a one-month lagged mutual fund holding based market beta sort. For most of the Morningstar categories, the standard alphas of the high beta mutual fund portfolios (B5) are smaller than those of the low beta mutual fund portfolios (B1). The exception is the Large Growth category, but the difference between B5 and B1 for this category is not significant.

Table 3.5 demonstrates the active alphas of quintile portfolios obtained from the one-month lagged mutual fund holding based market beta sort. The active alphas of the high beta mutual fund portfolios (B5) are larger than those of the low beta mutual fund portfolios (B1) for most of the investment categories. After controlling for different investment styles, high beta mutual funds still seem to display more skills after adjusting the passive exposure to stock betas.

3.5 Robustness

3.5.1 Alpha Estimation

The previous section estimates mutual fund active alpha as the intercept in a regression of mutual fund monthly benchmark adjusted mutual fund excess return. Here, we estimate the mutual fund active alphas using a rolling window method. Each month, we sort funds by their one-month lagged holding based market betas into quintiles to obtain 5 portfolios. Beginning with the 24th month during our 1980m4-2012m12 sample period, we estimate the standard alphas over the previous 24 months at each month. We calculate t-statistics with the Newey-West (1987) correction for the time-series correlation with 12 lags. Panel A of Table 3.6 shows the standard alphas of 5 mutual fund portfolios sorted by one-month lagged holding based market beta using the rolling window method. The negative relationship between the standard alpha and holding based market beta is not as obvious as the non-rolling window estimation result in Section 3.4, indicating that this relationship is not robust to different estimation methods. Panel B of Table 3.6 shows the standard alphas of the 5 matching passive benchmark stock portfolios.[2] The differences in standard alphas between the top beta benchmark stock portfolio and the bottom beta benchmark stock portfolio are statistically significant for all factor models.

Table 3.7 demonstrates the active alphas of quintile portfolios obtained from the one-month lagged mutual fund holding based market beta sort. The active alphas of the high beta mutual fund portfolio (B5) are larger than those of the low beta mutual fund portfolio (B1) for all factor models.

[2]We restrict the stock to appear in the Thomoson Reuters Mutual Fund Holding Database for the specific month.

3.5.2 Stock Sample

In Section 3.4, we restrict our stock universe to the stocks reported in the Thomson Reuters Mutual Fund Holding database. The reason for this exclusion is that mutual funds could not hold some stocks because of certain stock characteristics. As a robustness check, we relax this requirement by using all CRSP-listed stocks to form the matching passive stock benchmark for mutual funds. In Panel A of the Table 3.8, we estimate mutual fund active alpha as the intercept in a regression of mutual fund monthly benchmark adjusted excess return. To calculate the benchmark adjusted mutual fund return, we subtract the returns of a benchmark stock portfolio from mutual fund gross returns. The passive benchmark stock portfolios are formed by matching beta ranges of mutual fund portfolios using all CRSP-listed stock. Similar to the results in Section 3.4.2, we still find that active alpha monotonically increase with mutual fund holding beta.

3.6 Conclusion

This paper examines whether high beta mutual funds are associated with high alphas or low alphas. We first find that high beta is associated with low mutual fund standard alpha, which is similar to the findings for various assets in Frazzini and Pedersen (2014). Next, we explore the relationship between mutual fund beta and active alpha, which is defined as the difference between a mutual fund's standard alpha and the matching stock alpha. We document that the active alphas almost monotonically increase in beta. After adjusting mutual fund returns by a passive stock benchmark, the high beta mutual funds appear to have more skills.

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Figure 3.1: Mutual Fund Holding Based Betas

This figure is the histogram of mutual fund holding based betas. First, we estimate the factor loadings for each stock. For each month, we use previous 12-month daily stock return data to estimate the factor loadings for stocks. Following Frazzini and Pedersen (2014), we estimate volatilities and correlations separately to account for the fact that correlations move more slowly than volatilities. Our estimated market beta for security i is given by $\hat{\beta}_i^{MKT} = \hat{\rho}_{im}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$ where $\hat{\sigma}_i$and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their correlation. We use one-day log returns to estimate volatilities and overlapping three-day log returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} ln(1 + r_{t+k}^{i})$, for correlation to control for non-synchronous trading. Second, the mutual fund holding based beta for fund j during month t could be calculated as:$Fund\beta_j = \sum_{i=1}^{N_j} w_{i,j,t}\beta_{it}$. The sample period is from 1980 to 2014.

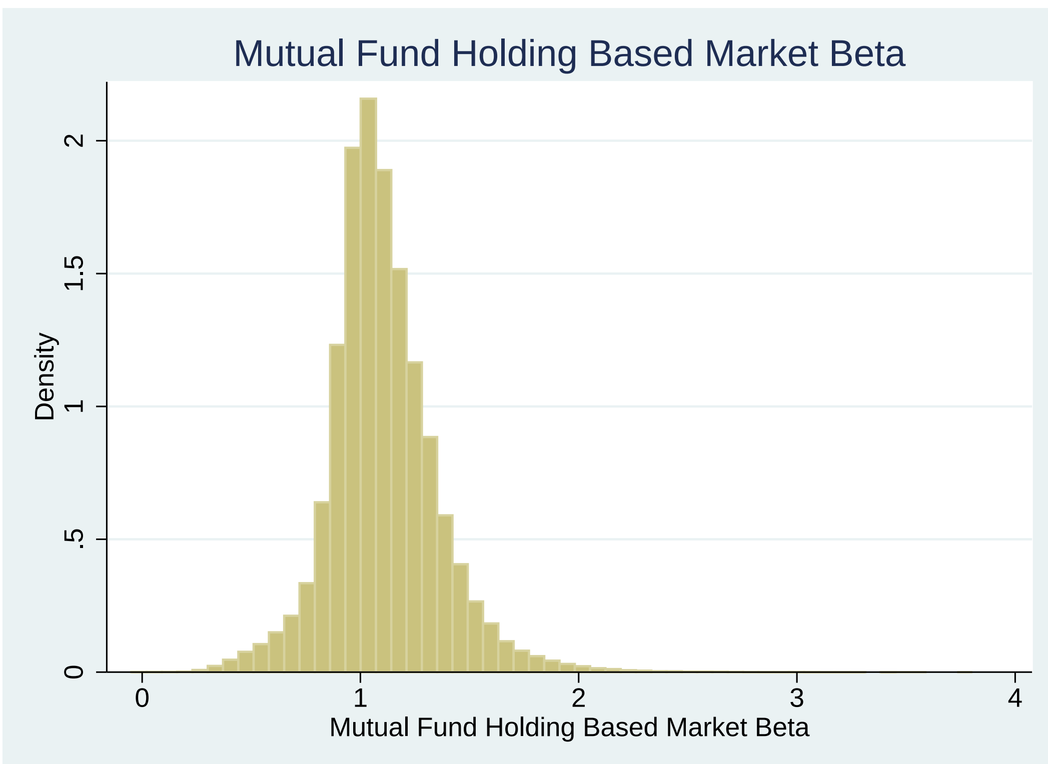

Figure 3.2: Matched Stock Betas

This figure is the histogram of stock betas which falls within the range of mutual funds' betas. First, we estimate the factor loadings for each stock. At the end of each calendar month, we use previous 12-month daily stock return data to estimate the factor loadings for stocks. Following Frazzini and Pedersen (2014), we estimate volatilities and correlations separately to account for the fact that correlations move more slowly than volatilities. Our estimated market beta for security i is given by$\hat{\beta}_i^{MKT} = \hat{\rho}_{im}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$ where $\hat{\sigma}_i$and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their correlation. We use one-day log returns to estimate volatilities and overlapping three-day log returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} ln(1+r_{t+k}^i)$, for correlation to control for non-synchronous trading. Second, the mutual fund holding based factor loadings for fund j during month t could be calculated as:$Fund\beta_j = \sum_{i=1}^{N_j} w_{i,j,t}\beta_{it}$. Third, we plot the stock factor loadings which falls within the range of mutual funds' factor loadings. The sample includes all CRSP-listed stock from 1980 to 2014 for the top panal. The sample includes all stocks appeard in Thomoson Reuters Mutual Fund Holding database from 1980 to 2014 for the bottom panal.

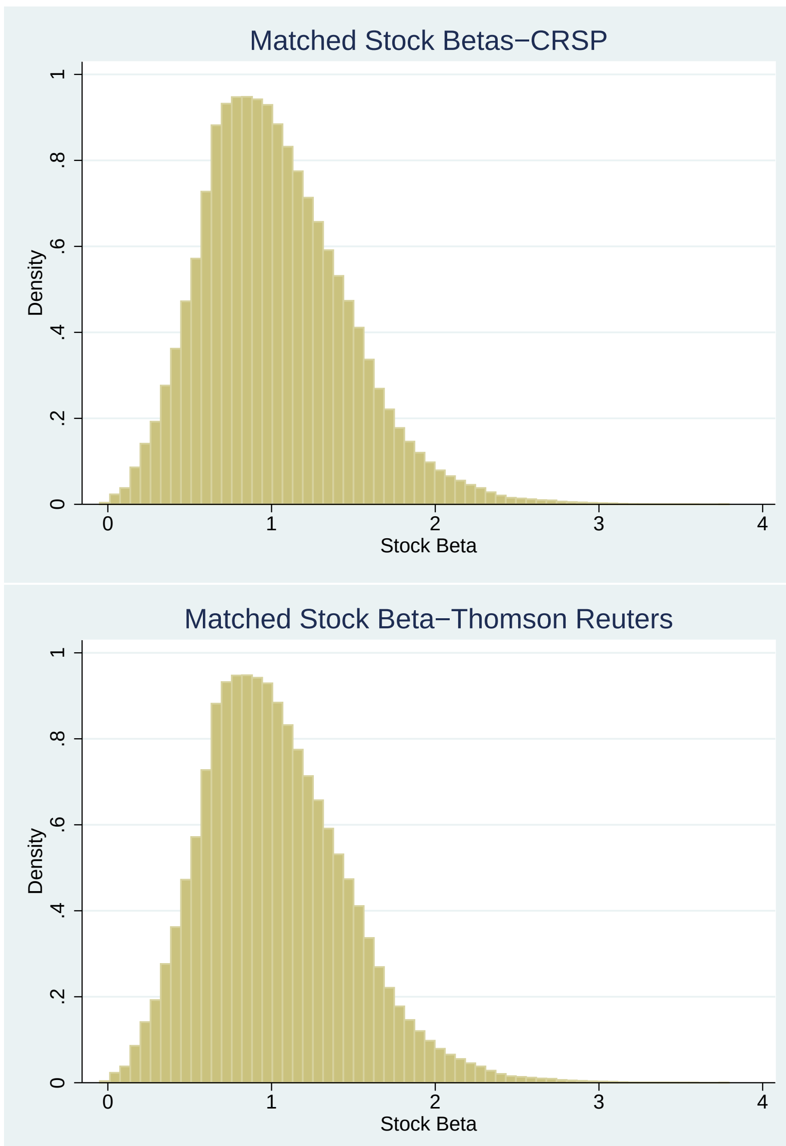

Table 3.1: Mutual Fund Summary Statistics

In Table 1, we sort funds by one-month lagged mutual fund holding based market beta into quintile and report the summary statistics for the five portfolios. The sample period is 1980m4-2014m12. The unit of observation is fund-month. In the second column of Table 1, we show the average of holding based beta for each portolios. To calculate the holding based market beta, we weight each stock-level factor loading according to its dollar weight in the most recent fund portfolio holdings.The third column reports the mutual fund gross returns. Mutual fund gross returns are calculate by buying the number of shares of each CRSP listed stock held by the fund on the first day of each quarter and holding the portfolio until the first day of the following quarter. We winsorize gross returns at the 0.5th and 99.5th percentiles. We report the retuns of passive benchmark porfolios for each quintles of mutual funds in the fourth column. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) The first criteria is that the stocks are hold by at least one mutual fund in a given month. 2) The second criteria is that the stocks match mutual fund holding based market beta. The fifth column reports mutual fund active return which is a bechmark adjusted return by taking the difference of the gross returns in column 3 and the bechmark returns in column 4. T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Beta Group (1)	Holding Based Beta (2)	Gross Return (%/month) (3)	Benchmark Return (%/month) (4)	Active Return (3)-(4)	t-stat for (3)-(4)
B1	0.83	1.18	1.33	-0.15 *	(-1.75)
B2	0.98	1.15	1.34	-0.20	(-1.60)
B3	1.08	1.14	1.31	-0.17	(-1.21)
B4	1.20	1.17	1.29	-0.12	(-0.85)
B5	1.42	1.17	1.12	0.04	(0.23)

Table 3.2: Standard Alphas of Mutual Fund Portfolios and Passive Benchmark Stock Portfolios

Panel A reports statistics for standard alphas of quintile portfolios obtained from univariate sorts by mutual fund holding based market beta. We weight each stock-level factor loading according to its dollar weight in the most recent fund portfolio holdings to calculate the monthly fund-level holding based factor loading. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Mutual fund standard alpha is the intercept in a regression of mutual fund monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. Panel B reports the standard alphas for the passive beckmark stock portfolios which are formed basis on the beta range of mutual fund portfolio. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) The stocks are hold by at least one mutual fund in the given month; 2) The stocks match the mutual fund holding based market beta. All alphas are in monthly percent. T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panal A: Mutual Fund Standard Alpha

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	0.24***	(3.48)	0.11*	(1.95)	0.13**	(2.17)	0.12**	(1.97)
B2	0.12**	(2.50)	0.05	(1.11)	0.06	(1.46)	0.06	(1.30)
B3	0.06	(1.47)	0.04	(1.23)	0.04	(1.04)	0.03	(0.93)
B4	0.01	(0.26)	0.05	(1.14)	0.04	(0.81)	0.04	(0.89)
B5	-0.11	(-0.99)	0.03	(0.40)	0.02	(0.25)	0.04	(0.55)
B5-B1	-0.35**	(-2.41)	-0.08	(-0.76)	-0.11	(-0.99)	-0.07	(-0.67)

Panal B: Matching Stock Alpha

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	0.37***	(3.37)	0.24***	(3.12)	0.31***	(4.07)	0.30***	(3.82)
B2	0.20	(1.61)	0.12	(1.58)	0.22***	(2.85)	0.20***	(2.66)
B3	0.10	(0.70)	0.07	(0.81)	0.19**	(2.32)	0.16**	(2.00)
B4	0.02	(0.10)	0.03	(0.31)	0.17*	(1.79)	0.15	(1.56)
B5	-0.38*	(-1.79)	-0.26*	(-1.84)	0.01	(0.07)	-0.03	(-0.21)
B5-B1	-0.75***	(-3.90)	-0.50***	-3.18	-0.30**	(-1.99)	-0.32**	(-2.09)

Table 3.3: Mutual Fund Active Alphas: Univariate Market Beta Sorts

This table reports statistics for mutual fund active alphas of quintile portfolios obtained from univariate sorts of holding based market beta. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Then, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) the stocks are hold by at least one mutual fund in the given month. 2) the stocks match the mutual fund holding based market beta.To calculate mutual fund benchmark adjusted return, we subtract the returns of a passive benchmark stock portfolio from mutual fund gross returns. Mutual fund active alpha is the intercept in a regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. All active alphas are in monthly percent.T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	-0.13	(-1.52)	-0.13**	(-2.04)	-0.19***	(-2.94)	-0.18***	(-2.82)
B2	-0.08	(-0.68)	-0.07	(-0.97)	-0.15**	(-2.00)	-0.14*	(-1.89)
B3	-0.04	(-0.31)	-0.02	(-0.27)	-0.15*	(-1.69)	-0.13	(-1.44)
B4	0.00	(-0.01)	0.02	(0.16)	-0.14	(-1.26)	-0.11	(-1.03)
B5	0.27	(1.59)	0.29**	(1.96)	0.01	(0.09)	0.07	(0.52)
B5-B1	0.41***	(3.05)	0.42***	(3.19)	0.20	(1.62)	0.25**	(2.05)

Table 3.4: Style Analysis: Mutual Fund Standard Alphas

This table reports statistics for standard alphas of nine Monrningstar style catogeries. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Mutual fund standard alpha is the intercept in a regression of mutual fund monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. All alphas are in monthly percent. T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Style	Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
Small Value	B1	0.33***	(2.68)	0.13*	(1.90)	0.14**	(2.04)	0.12	(1.67)
Small Value	B2	0.38***	(2.98)	0.18**	(2.16)	0.21**	(2.51)	0.20**	(2.37)
Small Value	B3	0.16	(1.26)	-0.03	(-0.29)	0.00	(0.00)	0.01	(0.13)
Small Value	B4	0.21	(1.53)	0.05	(0.59)	0.08	(0.80)	0.08	(0.84)
Small Value	B5	0.10	(0.69)	0.01	(0.10)	0.06	(0.60)	0.10	(0.90)
Small Value	B5-B1	-0.16	(-1.41)	-0.07	(-0.66)	-0.01	(-0.1)	0.04	(0.37)
Small Growth	B1	0.23**	(2.01)	0.18**	(2.56)	0.15**	(2.11)	0.15**	(2.09)
Small Growth	B2	-0.01	(-0.10)	0.05	(0.60)	-0.01	(-0.11)	0.01	(0.14)
Small Growth	B3	-0.10	(-0.66)	0.00	(-0.04)	-0.05	(-0.50)	-0.03	(-0.30)
Small Growth	B4	-0.16	(-1.03)	-0.05	(-0.57)	-0.08	(-0.84)	-0.05	(-0.54)
Small Growth	B5	-0.32*	(-1.79)	-0.15	(-1.25)	-0.15	(-1.26)	-0.11	(-0.89)
Small Growth	B5-B1	-0.55***	(-3.96)	-0.33***	(-2.77)	-0.30**	(-2.51)	-0.26**	(-2.14)
Small Blend	B1	0.27**	(2.07)	0.15	(1.53)	0.17*	(1.74)	0.16	(1.61)
Small Blend	B2	0.16	(1.27)	0.05	(0.55)	0.07	(0.79)	0.07	(0.79)
Small Blend	B3	0.26**	(2.13)	0.16**	(2.18)	0.15**	(2.00)	0.14*	(1.86)
Small Blend	B4	0.05	(0.45)	-0.01	(-0.13)	0.00	(-0.03)	-0.01	(-0.11)
Small Blend	B5	-0.09	(-0.64)	-0.10	(-1.14)	-0.09	(-1.00)	-0.08	(-0.87)
Small Blend	B5-B1	-0.30**	(-2.22)	-0.19	(-1.57)	-0.20*	(-1.67)	-0.18	(-1.50)
Mid-Cap Value	B1	0.38***	(3.50)	0.17**	(1.96)	0.19**	(2.19)	0.14	(1.60)
Mid-Cap Value	B2	0.20**	(2.12)	0.02	(0.24)	0.06	(0.79)	0.02	(0.22)
Mid-Cap Value	B3	0.18***	(1.97)	0.02	(0.21)	0.05	(0.69)	0.02	(0.28)
Mid-Cap Value	B4	0.22***	(2.57)	0.07	(0.87)	0.12	(1.68)	0.11	(1.43)
Mid-Cap Value	B5	0.16*	(1.82)	0.05	(0.62)	0.10	(1.27)	0.07	(0.93)
Mid-Cap Value	B5-B1	-0.22***	(-1.96)	-0.11	(-1.12)	-0.09	(-0.83)	-0.06	(-0.62)
Mid-Cap Growth	B1	0.12	(1.54)	0.13**	(2.01)	0.05	(0.88)	0.05	(0.76)
Mid-Cap Growth	B2	0.04	(0.41)	0.12*	(1.89)	0.05	(0.88)	0.05	(0.83)
Mid-Cap Growth	B3	-0.02	(-0.19)	0.11	(1.63)	0.07	(0.98)	0.07	(0.97)
Mid-Cap Growth	B4	0.00	(-0.02)	0.17**	(2.05)	0.13	(1.51)	0.13	(1.56)
Mid-Cap Growth	B5	-0.19	(-1.22)	0.05	(0.49)	0.03	(0.32)	0.04	(0.40)
Mid-Cap Growth	B5-B1	-0.31**	(-2.23)	-0.08	(-0.69)	-0.02	(-0.18)	0.00	(-0.03)
Mid-Cap Blend	B1	0.24***	(2.90)	0.11	(1.5)	0.13*	(1.74)	0.11	(1.51)
Mid-Cap Blend	B2	0.22***	(3.05)	0.13**	(2.05)	0.16**	(2.43)	0.15**	(2.21)
Mid-Cap Blend	B3	0.18***	(2.58)	0.13	(2.17)	0.14**	(2.19)	0.13**	(2.01)
Mid-Cap Blend	B4	0.08	(1.17)	0.06	(0.98)	0.05	(0.89)	0.04	(0.67)
Mid-Cap Blend	B5	0.01	(0.16)	0.05	(0.66)	0.09	(1.14)	0.08	(0.99)
Mid-Cap Blend	B5-B1	-0.23*	(-1.87)	-0.06	(-0.54)	-0.04	(-0.35)	-0.03	(-0.30)

Table 3.4 continue.

Style	Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
Large Value	B1	0.27***	(3.10)	0.12*	(1.73)	0.12*	(1.75)	0.12*	(1.70)
Large Value	B2	0.18**	(2.36)	0.03	(0.61)	0.08	(1.34)	0.07	(1.21)
Large Value	B3	0.10	(1.47)	-0.03	(-0.61)	0.01	(0.14)	0.01	(0.27)
Large Value	B4	0.08	(1.30)	-0.02	(-0.36)	0.02	(0.41)	0.03	(0.63)
Large Value	B5	-0.02	(-0.30)	-0.08	(-1.48)	-0.03	(-0.59)	-0.02	(-0.38)
Large Value	B5-B1	-0.28***	(-3.27)	-0.20**	(-2.42)	-0.15	(-1.86)	-0.14	(-1.67)
Large Growth	B1	0.10*	(1.76)	0.13**	(2.40)	0.11*	(1.93)	0.11	(1.97)
Large Growth	B2	0.04	(0.82)	0.14***	(3.12)	0.11**	(2.41)	0.12***	(2.59)
Large Growth	B3	-0.03	(-0.43)	0.10	(1.70)	0.07	(1.17)	0.08	(1.40)
Large Growth	B4	-0.03	(-0.34)	0.15**	(2.27)	0.11	(1.63)	0.12*	(1.86)
Large Growth	B5	-0.10	(-0.78)	0.14	(1.56)	0.13	(1.43)	0.16*	(1.71)
Large Growth	B5-B1	-0.20	(-1.55)	0.01	(0.10)	0.03	(0.25)	0.05	(0.47)
Large Blend	B1	0.15***	(2.71)	0.08	(1.62)	0.09*	(1.82)	0.09*	(1.84)
Large Blend	B2	0.08**	(2.14)	0.05	(1.56)	0.07**	(2.22)	0.07**	(2.25)
Large Blend	B3	0.02	(0.62)	0.01	(0.53)	0.02	(0.66)	0.02	(0.83)
Large Blend	B4	0.03	(1.03)	0.05	(1.57)	0.04	(1.35)	0.05	(1.53)
Large Blend	B5	-0.02	(-0.46)	0.03	(0.64)	0.06	(1.17)	0.08	(1.57)
Large Blend	B5-B1	-0.18**	(-2.04)	-0.04	(-0.61)	-0.03	(-0.37)	-0.01	(-0.12)

Table 3.5: Style Analysis: Mutual Fund Active Alphas

This table reports statistics for mutual fund active alphas for nine Monrningstar style catogeries. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Then, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) the stocks are hold by at least one mutual fund in the given month. 2) the stocks match the mutual fund holding based market beta.To calculate mutual fund benchmark adjusted return, we subtract the returns of a passive benchmark stock portfolio from mutual fund gross returns. Mutual fund active alpha is the intercept in a regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. All active alphas are in monthly percent.T-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Style	Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
Small Value	B1	-0.06	(-0.66)	-0.11	(-1.24)	-0.19**	(-2.37)	-0.21**	(-2.52)
Small Value	B2	0.08	(0.87)	0.05	(0.54)	-0.04	(-0.48)	-0.04	(-0.45)
Small Value	B3	0.05	(0.50)	0.00	(-0.02)	-0.07	(-0.72)	-0.07	(-0.70)
Small Value	B4	0.13	(1.15)	0.08	(0.74)	0.00	(-0.03)	0.01	(0.12)
Small Value	B5	0.17	(1.47)	0.12	(1.10)	0.01	(0.05)	0.05	(0.49)
Small Value	B5-B1	0.23**	(2.05)	0.23**	(2.07)	0.20*	(1.78)	0.26**	(2.37)
Small Growth	B1	0.05	(0.49)	0.07	(0.73)	-0.08	(-0.89)	-0.06	(-0.63)
Small Growth	B2	-0.08	(-0.59)	-0.02	(-0.16)	-0.23*	(-1.74)	-0.16	(-1.25)
Small Growth	B3	-0.10	(-0.62)	-0.03	(-0.19)	-0.28	(-1.9)	-0.25	(-1.69)
Small Growth	B4	-0.01	(-0.09)	0.03	(0.19)	-0.19	(-1.3)	-0.12	(-0.85)
Small Growth	B5	0.04	(0.21)	0.09	(0.47)	-0.19	(-1.12)	-0.12	(-0.69)
Small Growth	B5-B1	-0.01	(-0.05)	0.02	(0.11)	-0.11	(-0.81)	-0.06	(-0.45)
Small Blend	B1	-0.12	(-1.27)	-0.12	(-1.28)	-0.20**	(-2.16)	-0.20**	(-2.10)
Small Blend	B2	0.04	(0.43)	0.02	(0.24)	-0.08	(-0.89)	-0.07	(-0.75)
Small Blend	B3	0.13	(1.22)	0.12	(1.12)	-0.01	(-0.13)	0.01	(0.07)
Small Blend	B4	-0.10	(-0.75)	-0.11	(-0.9)	-0.24	(-2.00)	-0.23*	(-1.90)
Small Blend	B5	0.12	(0.87)	0.09	(0.66)	-0.05	(-0.40)	-0.01	(-0.11)
Small Blend	B5-B1	0.24**	(2.12)	0.22	(1.09)	0.16	(1.37)	0.19*	(1.66)
Mid-Cap Value	B1	0.01	(0.07)	-0.04	(-0.43)	-0.09	(-0.96)	-0.12	(-1.22)
Mid-Cap Value	B2	-0.14	(-1.12)	-0.15	(-1.70)	-0.23**	(-2.54)	-0.24***	(-2.69)
Mid-Cap Value	B3	-0.07	(-0.05)	-0.09	(-0.9)	-0.15	(-1.54)	-0.16	(-1.64)
Mid-Cap Value	B4	0.11	(0.87)	0.05	(0.53)	0.03	(0.36)	0.02	(0.23)
Mid-Cap Value	B5	0.17	(1.08)	0.09	(0.77)	-0.03	(-0.25)	-0.02	(-0.13)
Mid-Cap Value	B5-B1	0.16	(1.29)	0.12	(1.01)	0.06	(0.47)	0.10	(0.79)
Mid-Cap Growth	B1	-0.10	(-0.89)	-0.05	(-0.5)	-0.19	(-2.1)	-0.17*	(-1.84)
Mid-Cap Growth	B2	-0.01	(-0.06)	0.05	(0.38)	-0.17	(-1.39)	-0.15	(-1.22)
Mid-Cap Growth	B3	0.05	(0.29)	0.10	(0.69)	-0.10	(-0.68)	-0.05	(-0.38)
Mid-Cap Growth	B4	0.18	(1.06)	0.26*	(1.72)	0.06	(0.42)	0.09	(0.57)
Mid-Cap Growth	B5	0.21	(1.18)	0.27	(1.60)	-0.02	(-0.14)	0.01	(0.04)
Mid-Cap Growth	B5-B1	0.31***	(2.70)	0.31***	(2.69)	0.17	(1.49)	0.18	(1.53)
Mid-Cap Blend	B1	-0.07	(-0.73)	-0.08	(-1.12)	-0.15**	(-2.09)	-0.15**	(-2.01)
Mid-Cap Blend	B2	0.02	(0.18)	0.03	(0.31)	-0.04	(-0.45)	-0.05	(-0.56)
Mid-Cap Blend	B3	0.11	(0.84)	0.10	(1.01)	-0.02	(-0.23)	0.00	(0.02)
Mid-Cap Blend	B4	0.03	(0.19)	0.02	(0.23)	-0.10	(-0.94)	-0.09	(-0.88)
Mid-Cap Blend	B5	0.24	(1.54)	0.22	(1.63)	0.02	(0.14)	0.04	(0.33)
Mid-Cap Blend	B5-B1	0.31***	(2.65)	0.30***	(2.58)	0.17	(1.49)	0.19	(1.66)

Table 3.5 continue.

Style	Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
Large Value	B1	-0.12	(-0.92)	-0.12	(-1.52)	-0.19**	(-2.34)	-0.18**	(-2.22)
Large Value	B2	-0.05	(-0.36)	-0.07	(-0.86)	-0.13	(-1.61)	-0.13	(-1.55)
Large Value	B3	-0.13	(-0.88)	-0.15*	(-1.73)	-0.21**	(-2.31)	-0.19**	(-2.09)
Large Value	B4	-0.12	(-0.85)	-0.14*	(-1.77)	-0.18**	(-2.26)	-0.17**	(-2.14)
Large Value	B5	-0.06	(-0.36)	-0.09	(-0.96)	-0.21**	(-2.14)	-0.17*	(-1.74)
Large Value	B5-B1	0.06	(0.60)	0.03	(0.32)	-0.02	(-0.17)	0.01	(0.15)
Large Growth	B1	-0.14	(-0.98)	-0.09	(-0.93)	-0.18*	(-1.83)	-0.15	(-1.49)
Large Growth	B2	-0.03	(-0.19)	0.04	(0.34)	-0.11	(-0.99)	-0.08	(-0.69)
Large Growth	B3	0.08	(0.42)	0.13	(0.97)	-0.03	(-0.26)	0.01	(0.05)
Large Growth	B4	-0.02	(-0.12)	0.05	(0.35)	-0.15	(-1.08)	-0.11	(-0.78)
Large Growth	B5	0.28	(1.45)	0.36**	(2.25)	0.09	(0.61)	0.13	(0.89)
Large Growth	B5-B1	0.42***	(3.38)	0.45***	(3.60)	0.27**	(2.26)	0.28**	(2.32)
Large Blend	B1	-0.17	(-1.28)	-0.15*	(-1.90)	-0.19**	(-2.40)	-0.17**	(-2.12)
Large Blend	B2	-0.09	(-0.56)	-0.10	(-1.03)	-0.18*	(-1.84)	-0.14	(-1.49)
Large Blend	B3	-0.20	(-1.23)	-0.17*	(-1.74)	-0.26***	(-2.64)	-0.23**	(-2.35)
Large Blend	B4	-0.10	(-0.60)	-0.08	(-0.69)	-0.22**	(-2.03)	-0.18*	(-1.67)
Large Blend	B5	0.13	(0.73)	0.13	(1.02)	-0.09	(-0.78)	-0.04	(-0.33)
Large Blend	B5-B1	0.29***	(2.81)	0.27***	(2.62)	0.10	(1.03)	0.13	(1.33)

Table 3.6: Standard Alpha of Mutual Fund Portfolios and Passive Benchmark Stock Portfolios -Rolling Window Estimation

Panel A reports statistics for standard alphas estimated by 24-month rolling window regression. Each month, we sort funds by one-month lagged holding based market beta into quintile to obtain 5 portfolios. We weight each stock-level factor loading according to its dollar weight in the most recent fund portfolio holdings to calculate the monthly fund-level statistic. Beginning with the 24th month during our 1980m4-2012m12 sample period, we estimate the standard alpha over the previous 24 months at each month. Mutual fund standard alpha is the intercept in a rolling regression of mutual fun monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. Panel B reports the standard alphas for the passive benchmark stock portfolios which are formed basis on the beta range of mutual fund portfolio. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) The stocks are hold by at least one mutual fund in the given month; 2) The stocks match the mutual fund holding based market beta. The standard alphas for the passive benchmark is estimated using 24 month rolling window regression as well. All alphas are in monthly percent. We use Newey-West (1987) standard errors with twelve lags; t-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panal A: Mutual Fund Standard Alpha

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	0.19***	(2.90)	0.08***	(3.54)	0.09***	(4.11)	0.08***	(3.81)
B2	0.08*	(1.84)	0.04	(1.41)	0.05**	(2.07)	0.06**	(2.18)
B3	0.03	(1.02)	0.04*	(1.66)	0.04	(1.54)	0.05*	(1.87)
B4	0.00	(-0.03)	0.06*	(1.83)	0.05	(1.56)	0.07**	(2.06)
B5	-0.11	(-1.42)	0.09*	(1.65)	0.05	(1.06)	0.08	(1.60)
B5-B1	-0.30***	(-2.60)	0.01	(0.11)	-0.03	(-0.61)	-0.01	(-0.14)

Panal B: Matching Stock Alpha

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	0.35***	(2.72)	0.23***	(3.60)	0.25***	(4.12)	0.24***	(3.80)
B2	0.20	(1.40)	0.13*	(1.89)	0.14**	(2.21)	0.14**	(2.33)
B3	0.12	(0.86)	0.09	(1.27)	0.09	(1.48)	0.06	(1.18)
B4	0.06	(0.44)	0.07	(1.11)	0.10*	(1.69)	0.09	(1.62)
B5	-0.25	(-1.59)	-0.12	(-1.40)	-0.08	(-1.07)	-0.06	(-0.91)
B5-B1	-0.61***	(-5.31)	-0.35***	(-4.05)	-0.33***	(-4.09)	-0.30***	(-4.17)

Table 3.7: Mutual Fund Active Alpha-Rolling Window Estimation

This table reports statistics for mutual fund active alphas estimated by rolling window regression. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Then, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is a equal weighted portfolio of stocks which satisfies two criteria: 1) the stocks are hold by at least one mutual fund in the given month. 2) the stocks match the mutual fund holding based market beta.To calculate mutual fund benchmark adjusted return, we subtract the returns of a passive benchmark stock portfolio from mutual fund gross returns. Beginning with the 24th month during our 1980m4-2012m12 sample period, we estimate the active alpha over the previous 24 months at each month. Mutual fund active alpha is the intercept in a rolling regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. All active alphas are in monthly percent.We use Newey-West (1987) standard errors with twelve lags; t-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	-0.17*	(-1.88)	-0.15**	(-2.25)	-0.16***	(-2.68)	-0.16**	(-2.45)
B2	-0.12	(-0.97)	-0.09	(-1.25)	-0.08	(-1.26)	-0.09	(-1.29)
B3	-0.09	(-0.72)	-0.04	(-0.59)	-0.05	(-0.78)	-0.02	(-0.27)
B4	-0.06	(-0.53)	-0.02	(-0.23)	-0.06	(-0.86)	-0.03	(-0.42)
B5	0.15	(1.17)	0.21**	(2.21)	0.14*	(1.71)	0.14*	(1.81)
B5-B1	0.31***	(4.20)	0.36***	(4.86)	0.30***	(4.54)	0.30***	(4.69)

Table 3.8: Active Alphas Using CRSP Listed Stock Universe

This table reports statistics for mutual fund active alphas estimated by using the whole CRSP listed stock universe to form the passive stock benchmark. Each month, we sort funds by one-month lagged mutual fund holding based market beta into quintile to obtain 5 portfolios. Then, we form a passive benchmark stock portfolio for each mutual fund portfolio. The benchmark is a equal weighted portfolio of all CRSP-listed stocks which match the mutual fund holding based market beta.To calculate mutual fund benchmark adjusted return, we subtract the returns of a passive benchmark stock portfolio from mutual fund gross returns. In Panel A, the mutual fund active alpha is the intercept in a regression of mutual fund monthly benchmark adjusted excess return. The explanatory variables are the monthly returns from Fama and French (1993) size and value factors, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. In Panel B, we estimated active alpha using rolling window regressions. Beginning with the 24th month during our 1980m4-2012m12 sample period, we estimate the active alpha over the previous 24 months at each month. All active alphas are in monthly percent.We use Newey-West (1987) standard errors with twelve lags for the Panel B rolling window regression result; t-statistics are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Active Alpha - whole sample

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	-0.07	(-0.64)	-0.07	(-0.83)	-0.13	(-1.58)	-0.12	(-1.52)
B2	-0.03	(-0.23)	-0.03	(-0.34)	-0.11	(-1.28)	-0.11	(-1.26)
B3	0.04	(0.27)	0.05	(0.52)	-0.08	(-0.77)	-0.06	(-0.62)
B4	0.05	(0.33)	0.06	(0.51)	-0.10	(-0.80)	-0.08	(-0.65)
B5	0.31*	(1.69)	0.34**	(2.08)	0.05	(0.37)	0.11	(0.72)
B5-B1	0.38***	(2.81)	0.40***	(3.00)	0.18	(1.46)	0.23*	(1.85)

Panel B: Active Alpha - rolling window

Mkt Beta	CAPM		3 Factor		4 Factor		5 Factor	
B1	-0.11	(-1.10)	-0.06	(-0.70)	-0.08	(-1.07)	-0.07	(-0.88)
B2	-0.06	(-0.48)	-0.01	(-0.06)	-0.02	(-0.22)	-0.02	(-0.23)
B3	-0.02	(-0.12)	0.04	(0.41)	0.01	(0.14)	0.05	(0.67)
B4	-0.01	(-0.06)	0.07	(0.82)	0.01	(0.14)	0.04	(0.46)
B5	0.18	(1.33)	0.30***	(2.70)	0.22**	(2.23)	0.23**	(2.41)
B5-B1	0.29***	(3.91)	0.36***	(5.04)	0.30***	(4.52)	0.31***	(4.89)