How Would Hedge Fund Regulation Affect Investor Behavior? Implications for Systemic Risk

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Abstract

This paper studies investors' demand for hedge funds to examine an effect of regulation under policy debates which aims to enhance financial stability. Using fund-level characteristics data, we estimate a hedge fund demand which takes into account investors' heterogeneous taste for leverage usage. Our estimation results demonstrate 20% of investors positively evaluate leverage usage. We then conduct a policy simulation where regulators put a cap on the hedge funds' leverage, as proposed by the Financial Stability Board in 2012. Simulation results suggest that regulation would lower the total demand for hedge funds by 10%. In particular, regulation would lead to lower investments for highly leveraged funds and for risky strategies, which in turn, would reduce systemic risk.

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1 Introduction

After several large hedge funds' collapses such as Long-Term Capital Management (LTCM) or Amaranth Advisors, a hedge fund industry has drawn global attentions. A central concern for policy makers regarding the hedge funds industry is systemic risk – one failure of a large hedge fund may affect not only its investors, but also trading counterparties and creditors, including large financial institutions. As a consequence, it might trigger huge turmoil in financial markets. To prevent a wider collapse, for example, Federal Reserve Bank of New York organized a bail out of 3.6 billion dollars for LTCM. Those historical events lead to discussions on tighter regulations on hedge funds and the Financial Stability Board proposed a regulation on leverage usage.

While policy makers have continuously discussed regulating hedge funds, these funds provide unique investment opportunities to investors and liquidity to some particular financial markets. Hedge funds aim absolute returns, which are uncorrelated with the status of financial markets, by taking unique investment methods such as leverage usage short-selling. Therefore, direct regulations on hedge funds might remove unique features of hedge funds and decrease their demand.

This paper empirically studies such a trade-off between systemic risk and investors' demand for hedge funds. In particular, this paper attempts to quantify an impact of the proposed leverage cap regulation on investor behavior and derive its implications for systemic risk. To answer these questions, we exploit structural demand estimation technique, which is recent developments in Industrial Organization literature, to recover investors demand for hedge funds and simulate effects of hypothetical regulations.

To simulate investor behavior under the hypothetical scenario, we are required to estimate the hedge fund demand model of investors. In Lipper TASS hedge fund data, we can observe each hedge fund characteristics and the amount of the assets under management, which enables us to calculate the market share for each fund. We relate market share information to the hedge funds' characteristics, using techniques developed by Berry (1994) and Berry, Levinsohn and Pakes (1995), in order to recover investors utility function. This methodology is also utilized in finance literature: a seminal work done by Massa (2003) examines the demand for mutual funds and analyzed the industry structure.[1] Our current estimation

[1] Schroth (2006) studies the choice of underwriters and Dick (2008) studies consumers' choice of banking account. Gavazza (2011) studies mutual fund spillover effect.

results suggest that about 20% of investors prefer to invest in funds that use high leverage, while the rest of investors prefer low leveraged funds.

Using the estimated model, we conduct a counterfactual simulation where government regulate hedge funds leverage. More precisely, we limit the maximum leverage usage is equal to 1,000%, 500%, and 200%. Our simulation results suggest that the demand for hedge funds would decrease by about 10% in 200% case. In particular, the demand for hedge funds that use high leverage would drop sharply. However, it would also decrease two systemic risk factors: (1) as highly leveraged funds would lose their demand significantly and a distribution of fund size would be equalized than before, and (2) assets allocations to some risky strategies that are more likely to bankrupt than other funds would be decreased. Thus, we conclude that the proposed leverage regulation would reduce systemic risk significantly.

Hedge funds and risk are discussed in the existing literature. For example, Aragon and Strahan (2012) show that shortage of traders' funding liquidity decreased market liquidity in the Bankruptcy of Lehman Brothers. Dudley and Nimalendran (2012) also find that investors will harshly withdraw from poorly performing funds if those funds use more leverage and are less liquid. Furthermore, Ben-David, Franzoni and Moussawi (2012) find that hedge funds exited from the equity market en masse in 2007-2009 financial crisis due to redemption and margin calls. On the other hand, it is also reported that the hedge fund industry has vulnerable structures. Boyson et al. (2010) find that hedge funds returns are correlated outside fundamental change. Gupta and Liang (2005) discussed hedge funds' undercapitalization. Ang, Gorovyy and van Inwegen (2011) study hedge-fund leverage and its characteristics.

This paper is organized as follows: Section 2 describes the data and gives summary statistics and motivating facts for the modeling framework. In Section 3, we present the model and Section 4 depicts the estimation procedure. The estimation results are presented in Section 5. The effects of regulation change will be analyzed by counterfactual simulation in Section 6. Section 7 concludes.

2 Data and Systemic Risk Measures

2.1 Data and Characteristics of Hedge Funds

The data mainly come from the Lipper TASS hedge fund database, which is one of the most accurate representative of the hedge fund universe. Compared to other databases, this Lipper TASS database includes detailed fund characteristics such as leverage usage, redemption restrictions, trading instruments and so on. Therefore, this is one of the most suitable databases to conduct the demand analysis. To avoid issues with survivor bias, we use both the live and graveyard funds. As well, we include the fund of hedge funds for they are one of the popular strategies for investors. The sample period is from January 2007 to December 2011. We annualize monthly data, as in Massa (2003) or Gavazza (2011). We filter the data as follows: First we included the hedge funds whose domicile currency is US dollar to analyze investors behaviors in the U.S. Then, we exclude hedge funds which do not report asset size, rate of returns and fund characteristics. We assume that the alternative investment option for hedge funds investment is the total financial wealth not invested to hedge funds in the sample, which is taken from "*Flow of Funds Accounts of the United States, Annual Flows and Outstandings*" by the Board of the Governors of the Federal Reserve Bank, as Gavazza (2011) does. Table 1 depicts sample statistics. In the rest of this subsection, we describe more details of some important characteristics, such as leverage and redemption restrictions, which are listed in Table 1.

Leverage One of the main features of hedge funds is leverage usage. The leverage usage in Lipper TASS data is defined as portfolio/equity ratio. If this number is equal to one, then their portfolio size is equal to the size of assets under management (hereafter AUM) which is the amount of money that hedge fund has the right to claim a management or/and incentive fee. If this number exceeds one, then hedge funds manage more assets than what they originally have by using derivatives or borrowing money from other financial institutions collateralizing some of their assets.

Figure 1 shows leverage usage in ordinary time, labeled as *average leverage*, and historical maximum usage, labeled as *maximum leverage*. Around one third of hedge funds use leverage and some of them use extremely high leverage.[2] If high leveraged hedge funds failed, creditors

[2]This statistics of leverage usage coincides with an internal survey in European Central Bank (2005).

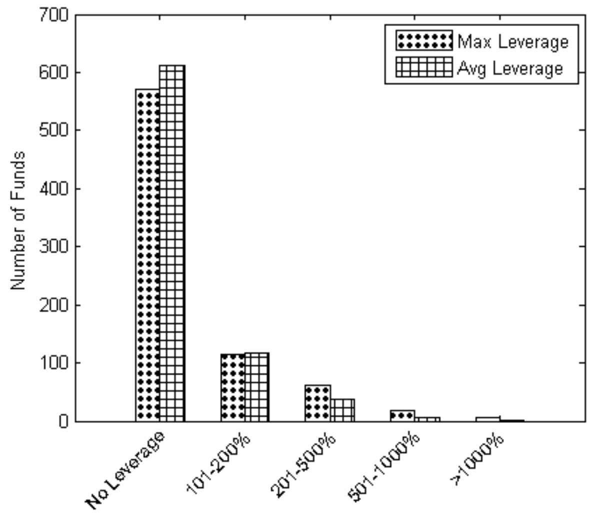
Table 1: Summary Statistics

	Mean	Std. Dev	Min	Max
Rate of Returns	0.0026	0.027	-0.783	0.104
S.D. of Rate of Returns	0.036	0.030	0	0.390
Minimum Investment (thousands)	1314	2527	0	50000
Management Fee (%)	1.431	0.858	0	20
Incentive Fee (%)	17.21	6.36	0	50
High Watermark	0.80	0.40	0	1
Leveraged	0.68	0.46	0	1
Max Leverage (%)	160.62	265.08	0	8000
Avg Leverage (%)	124.90	153.25	0	6000
Margin	0.33	0.47	0	1
Open End	0.46	0.50	0	1
Open to Public	0.25	0.43	0	1
Redemption Notice Period (Days)	45.47	28.59	0	180
Lockup Period (Month)	5.42	7.17	0	60

such as large banks or other financial counterparties would get a large loss and be destabilized. Therefore, highly leveraged funds can be considered as potential threat to financial stability.

Strategy According to Lipper TASS, there are three main categories of hedge funds. First, “arbitrage” hedge funds aim to make profits by arbitraging mispricing in asset markets. This category includes strategies called *convertible arbitrage*, *fixed income arbitrage* and so on. Second, “directional” hedge funds aim to make profits from direction of markets. This category includes strategy called *long/short equity*, *global macro*, *managed features*, *dedicated short bias* and so on. The main difference between traditional funds and hedge funds is that they use short positions and exposure to derivatives. Third, *event driven* hedge funds aim to make profits using some events such as mergers, restructuring and failures of firms. Furthermore, *Multi-strategy* uses other several strategies and *Fund of funds* invest in several other hedge funds. Figure 2 shows the breakdown of hedge funds in terms of their disclosed investment strategy in 2007. The graph shows that “Long/Short Equity” and “Fund of Funds” hedge funds are the predominant strategy in terms of number. However, in terms of assets under management, their market share is smaller, and this suggest that their asset

Figure 1: Leverage Usage



sizes are smaller than other strategies on average.

2.2 Measurements for Systemic Risk

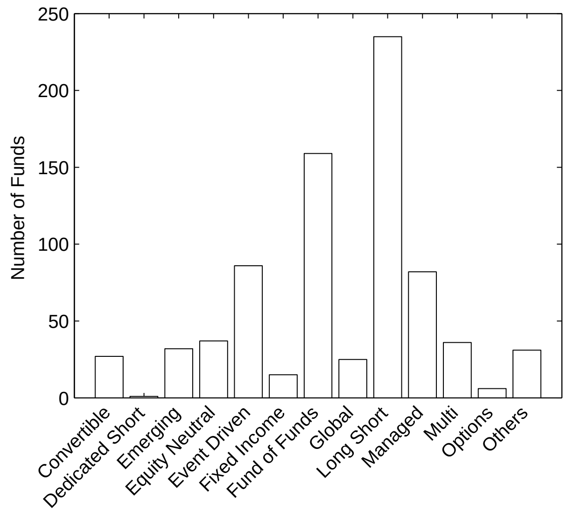
Systemic risk is an ambiguous concept and difficult to quantify. Taking advantage of our fund-level micro data, however, this study attempts quantify regulation effects on systemic risk through following three measures: (1) concentration, (2) asset allocation for risk strategies, (3) volatility index, as well as macro-level assets amounts in this industry.

Micro Measurement 1: Size Concentration One of the unique characteristics of the hedge fund industry is its concentration. The largest 1% of funds manage more than 20% of total assets in the industry. This feature becomes more prominent if we consider leveraged assets. To illustrate this concentration, we use *Herfindahl-Hirschman Curve*, inspired by *Herfindahl-Hirschman Index* (HHI) which is commonly used in Industrial Organization literature.

The left and right panel in Figure 4 show the market concentration with assets and assets multiplied by leverage in the industry, respectively.[3] We observe both curves skew down-

[3]First, we sort existing hedge funds by assets or assets multiplied by leverage, and divide them by the total size to compute their density functions. Then, we can easily obtain cumulative distribution functions by summing them up by ascending order. If we observe a 45 degree straight line in the graph, it implies that

Figure 2: Number of Funds and Market Share by Strategy in 2007



wards, implying top few percentage of funds manage a large fraction of assets or leveraged assets in the industry. We focus on how these Herfindahl-Hirschman Curves would change after the implementation of hedge fund regulation, as one of the systemic risk measurements.

Micro Measurement 2: Asset Allocations for Risky Strategies Some particular strategies typically use high leverage and are more likely to go bankrupt with large loss. Pointed out by Ferguson and Laster (2007), *Global Macro*, *Fixed Income Arbitrage* and *Multi-Strategy* were main strategies of the past large scale failures, accounted 33%, 30% and 28%, respectively. Therefore, the asset allocations for those risky strategies might serve as a good measurement of systemic risk.

Figure 5 shows shares of each strategy in terms of assets and leverage assets in 2007. Risky hedge funds such as global macro, fixed income arbitrage and multi-strategy account 21% of the industry assets under management, though they accounts much higher shares in terms of the leveraged asset size due to the high leverage usage.

every hedge fund has exactly same amount of assets.

Figure 3: Number of Funds and Market Share by Strategy in 2007

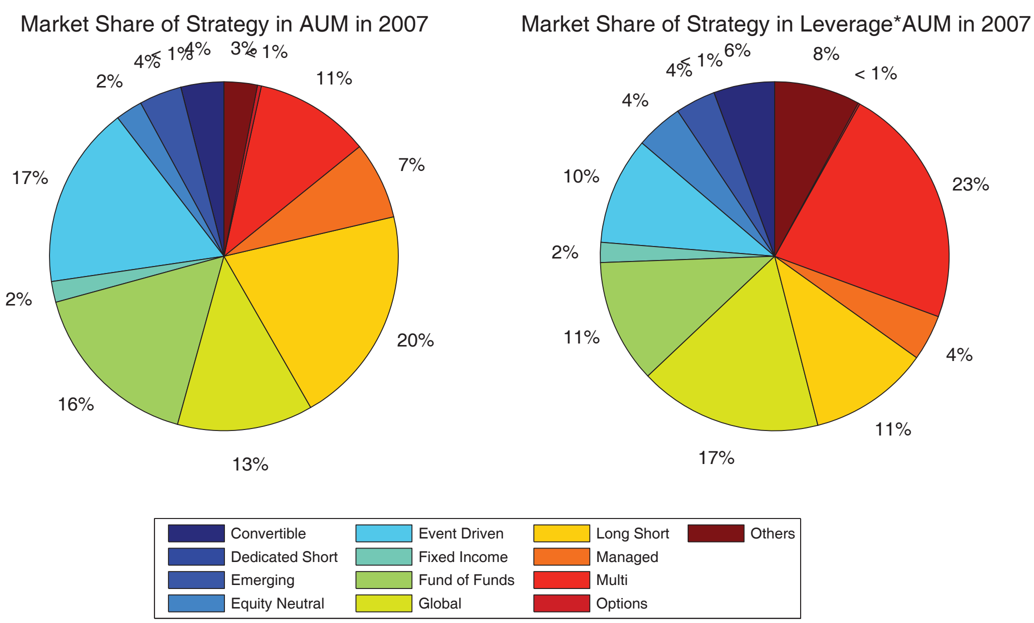
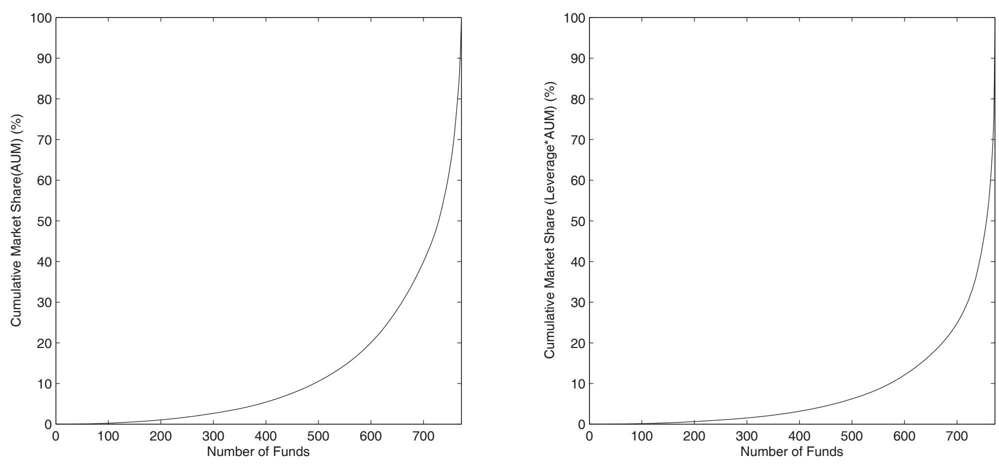


Figure 4: Concentration of Hedge Funds Assets

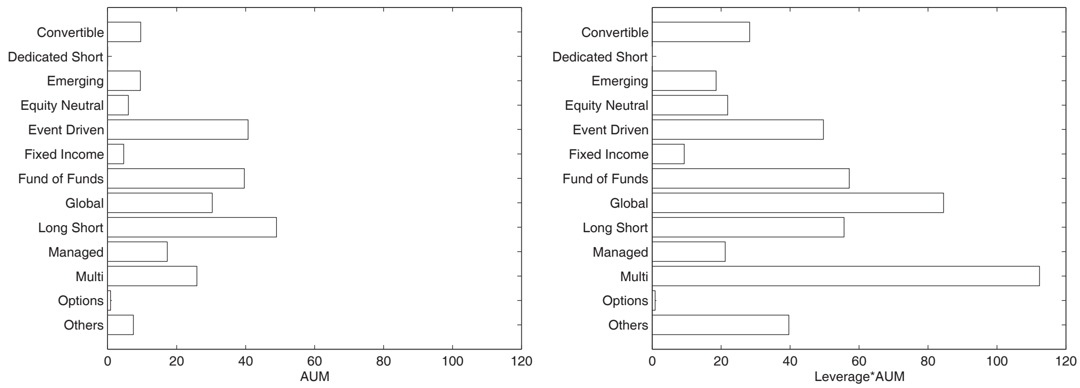


Note: The left panel shows asset under management, while the right panel shows assets under management multiplied by leverage. We use the sample in 2007 and the number of existing funds in 2007 is 772.

Micro Measurement 3: Weighted Average of Volatility Finally, we also consider the industry-level volatility defined as:

$$\text{Total Industry Volatility} = \sum_{j=1}^{J} \text{AUM}_j \times \text{Volatility}_j$$

Figure 5: Asset Allocations by Strategy in 2007



If assets in the hedge fund industry are concentrated to high volatility funds which potentially are likely to fail, their failures may affect to financial markets.

3 Model

3.1 Overview of the Model

Our final goal is examining effects of a set of regulations suggested by the *Financial Stability Board*. To do this, we are required to simulate asset distribution across hedge funds (market shares) under the regulations which are not implemented yet, implying that it is difficult to directly utilize standard regression analysis.[4] Therefore, we use a structural approach to tackle this problem, i.e., we recover the investors' utility function by modeling the investors hedge fund choice problem, and then simulate how their hedge fund choice would be changed under regulations.[5]

[4]For example, suppose we specify a relationship between funds asset size (market share) and the average leverage ratio, using a standard regression:

$$(\text{asset size})_j = \beta_0 + \beta_1(\text{ave. leverage})_j + \cdots + \epsilon_j.$$

From this regression, what we can infer is the (marginal) effect of average leverage ratio. Thus, if we want to know the asset size for fund j whose average leverage is not affected by regulations, this model is silent (or we can interpret zero asset size change). However, our intuition tells it is not the case, because some of funds might be a substitute for fund j and those funds are (negatively) affected by regulations, and thus some investors would invest fund j. In order to have such reasonable 'substitution patterns' across funds, we need to model investors' behavior.

[5]In order to fully take into account the equilibrium effects, we also need to model hedge funds behavior. We discuss this issue in Section 6.

More precisely, as the data include yearly aggregate-level market share and fund-level characteristics information, we use a methodology developed by Berry (1994) and Berry, Levinsohn and Pakes (1995) where they exploit the information contained in the market share.[6] In their methodology, each product is expressed as a bundle of characteristics. In our context, each hedge fund is characterized by the past realizations of return, some redemption restrictions, usage of the leverage, and so on. Then, we assume that each investor derives the utility from these characteristics of the hedge funds and purchase that gives the highest utility. As we observe multiple years of market shares, we have some variations in the investors choice set. Intuitively, observing the relatively higher market share for some particular funds, we can infer how investors valuate the fund characteristics. In other words, we can recover the investors' valuation for each characteristic of the hedge funds, using the variation in choice set as an identification source.

This methodology has been extensively used in Industrial Organization literature and has become popular in the last decade, as well as recent studies in finance. For instance, Massa (2003) uses this technique to recover investors' utility from mutual funds choice, and Schroth (2006) studies firms' choice of an underwriter.[7]

3.2 Investors' Behavior

Let j denote each hedge fund and $\mathcal{J}_t$ denote existing funds at time t. A vector of characteristics for each fund j is denoted by $\boldsymbol{X}_{jt}$, which includes two types of characteristics: (1) time-variant characteristics, and (2) time-invariant characteristics. The time-variant characteristics include the monthly- or quarterly-level returns, volatility of the returns, which would change over time. On the other hand, each fund's strategy, redemption notification period, or incentive and management fees usually do not change over time, and thus those characteristics would be considered as time-invariant characteristics. We assume each investor derives utility from these hedge funds' characteristics, $\boldsymbol{X}_{jt}$, and chooses a fund that

[6]Of course, if we had the investor-level portfolio data, we could have used different approach. However, such data is rarely available and we only have macro-level market share data for this study. One of the prominent features of their methodology is that we can recover the demand function from the data on market share and product characteristics.

[7]There are more studies using the similar technique.

give the highest utility defined by

$$u_{ijt} \;\; = \;\; \boldsymbol{X}_{jt}\boldsymbol{\beta}_i + \xi_j + \varepsilon_{ijt}, \tag{1}$$

where $\boldsymbol{\beta}_i = [\beta_{i,1}, \beta_{i,2}, \cdots, \beta_{i,M}]'$ denotes a $m-$dimensional heterogeneous coefficients vector for hedge fund characteristics, ξ_j denotes a hedge fund specific unobserved term and ε_{ijt} denotes a random utility shock. Notice that except ε_{ijt} the utility only depends on hedge fund brand j and time t.

The heterogeneous coefficients vector, $\boldsymbol{\beta}_i$, allows investors to have different taste. More precisely, we assume the following parametric assumption for each characteristics m:

$$\beta_{i,m} \;\; = \;\; \beta^o_m + \beta^u_m \nu_{i,m}, \quad \text{where } \nu_{i,m} \sim N(0,1) \tag{2}$$

where β^o_m denotes the average valuation for the characteristic m, β^u_m denotes the standard deviation for the valuation, and $\nu_{i,m}$ is an i.i.d. standard normal random variable.[8] As we see in Section 2, the data suggest non negligible fraction of hedge funds use leverage and there exist the demand for these funds, implying that some investors positively valuate the usage of leverage. Thus, even though investors valuate one of the characteristics – leverage – negatively on average, some people who have a positive shock, $\nu_{i,m}$, can have positive valuation for that characteristic. Notice that the standard homogeneous coefficients model can be expressed as one of the special case of this model by assuming $\beta^u_m = 0$ for every characteristic m.

Now, plugging the coefficients vector, equation (2), into the utility function, equation (1), we can rewrite the utility function as

$$u_{ijt} \;\; = \;\; \boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \boldsymbol{X}_{jt}\boldsymbol{\beta}^u_i + \xi_{jt} + \varepsilon_{ijt},$$

where $\boldsymbol{\beta}^o = [\beta^o_1, \cdots, \beta^o_M]'$ and $\boldsymbol{\beta}^u_i = [\beta^u_1 \nu_{i,1}, \cdots, \beta^u_M \nu_{i,M}]'$. Defining the *mean utility*, δ_{jt}, as a sum of two components, $\boldsymbol{X}_{jt}\boldsymbol{\beta}^o$, and ξ_j, which do not depend on investor i specific variables, and re-define $\boldsymbol{X}_{jt}\boldsymbol{\beta}^u_i$ as the *deviation from the mean*, μ_{ijt}. These expressions enable us to

[8] Alternatively, we can also express equation (2) as $\beta_{i,m} \sim N(\beta^o_m, (\beta^u_m)^2)$.

rearrange the indirect utility function as

$$\begin{aligned} u_{ijt} &= \underbrace{\boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \xi_j}_{\delta_{jt}} + \underbrace{\boldsymbol{X}_{jt}\boldsymbol{\beta}_i^u}_{\mu_{ijt}} + \varepsilon_{ijt}, \\ &= \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}. \end{aligned}$$

Moreover, when investors do not choose any hedge fund but outside options, $j = 0$, we assume that investor will obtain utility of zero, $\delta_{0t} = 0$, for normalization purpose. In other words, $u_{i0t} = \varepsilon_{i0t}$.

Assuming a Type I extreme value distribution for the disturbance term, the probability that investor i chooses hedge fund j at time t is given by:

$$\Pr(d_{i,t} = j | \{\boldsymbol{X}_{kt}, \xi_k\}_{k \in \mathcal{J}_t}) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt} + \mu_{ilt})},$$

where $d_{i,t}$ denotes the investor i's decision to choose hedge fund j at time t. Therefore, summing over investors' choice probability for fund j at time t, we can obtain the aggregate level market share as

$$s_{jt} = \int_{i \in \mathcal{I}} \Pr(d_{i,t} = j | \{\boldsymbol{X}_{kt}, \xi_k\}_{k \in \mathcal{J}_t}, \boldsymbol{\nu}_i) dF(\boldsymbol{\nu}). \tag{3}$$

No Heterogeneity Case In this study, we assume there exist heterogeneity in investors' preference. However, assuming that there does not exist heterogeneity, we can simplify the model and estimation procedure. First of all, the market share can be expressed as

$$s_{jt} = \frac{\exp(\delta_{jt})}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt})}, \tag{4}$$

because now we assume $\beta_m^u = 0$ for all m. This equation straightforwardly implies that if the mean utility level of hedge fund j increased, then the market share for hedge fund j would also increase. Similarly, we can also calculate the market share for outside option as

$$s_{0t} = \frac{1}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt})}. \tag{5}$$

Using the inversion technique developed by Berry (1994) – dividing both sides of equations (4) and (5), and taking logarithm – we can obtain the mean utility as

$$\begin{aligned}\log(s_{jt}) - \log(s_{0t}) &= \delta_{jt} \\ &= \boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \xi_{jt}. \end{aligned} \tag{6}$$

where the second equation is derived by the definition of δ_{jt}. Therefore, we can estimate the model with standard regression technique, assuming ξ_{jt} as residuals. Moreover, for the case of the nested logit model, equation (6) can be rewritten as

$$\log(s_{jt}) - \log(s_{0t}) = \boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \sigma \log(s_{j/g}) + \xi_{jt}, \tag{7}$$

where $s_{j/g}$ denotes the share within the same group.[9] Again, assuming ξ_{jt} as residuals, we can use the standard regression technique.

It is impossible, however, to estimate the model by linear regression when we have some endogeneity issues. Namely, if we believe that ξ_{jt} is correlated with some other variables in $\boldsymbol{X}_j$, linear regression estimates will be biased. Therefore, we need to use instrumental variables approach, which we discuss in Section 4.

4 Estimation

4.1 GMM-Type Estimation with Investors' Heterogeneity

We exploit an estimation method developed by Berry, Levinsohn and Pakes (1995) and Nevo (2001). As we demonstrate in Section 3, if the model does not include heterogeneity in investors' preference, we can estimate the model using a standard regression. It is, however, impossible to use it, if the model includes heterogeneity, as in equation (3). Therefore, we use simulation to obtain the market share:

$$s^S_{jt}(\boldsymbol{X}, \boldsymbol{\delta}) = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt} + \mu_{ilt})}, \tag{8}$$

[9] In a nested logit model, investors first choose one category of the funds and choose a fund among that category. The category can be strategy or location of the headquarters etc, which could be arbitrary. Moreover, the derivation for this equation is out of interest. Those who are interested in can see some standard references such as McFadden (1974) and Berry (1994).

by generating ns times of random numbers for $\boldsymbol{\nu}_i$, which enables us to calculate μ_{ijt}. As we know the market share of each funds, we can estimate the parameter by minimizing the distance between observed and predicted market shares:

$$\min_{\theta} \| \boldsymbol{s}_t^S(\boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{X}, \boldsymbol{\xi}; \boldsymbol{\beta}^o); \boldsymbol{\beta}^u) - \boldsymbol{s}_t^D \|,$$

where $\boldsymbol{s}_{jt}^D$ denotes a j dimensional vector of observed market share in the data and θ denotes a set of parameters. Although it is an intuitive way, this minimization is computationally expensive and we commonly use the estimation procedure developed by Berry, Levinsohn and Pakes (1995) and Nevo (2001) where they utilize the orthogonality conditions between the the structural error term, ξ, and a set of instruments.

As mentioned in Section 3, the structural error term, ξ_j is likely correlated with some other observed variables $\boldsymbol{X}_j$. In our context, ξ_j can be seen as unobserved fund manager's skill, for example. Then, we expect a good fund manager yields higher returns, implying that ξ_j will be correlated with the rate of returns. In order to take into account such endogeneity, we use instrumental variables approach. Specifically, simulated share equations (8) enable us to solve for $\boldsymbol{\delta}(\boldsymbol{X}, \boldsymbol{\xi}; \boldsymbol{\beta}^o)$, as we have J_t unknowns with J_t equations for each year:

$$\begin{gathered} s_{1t}^S(\boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{X}, \boldsymbol{\xi}; \boldsymbol{\beta}^o); \boldsymbol{\beta}^u) - s_{1t}^D = 0 \\ \vdots \\ s_{Jt}^S(\boldsymbol{X}, \boldsymbol{\delta}(\boldsymbol{X}, \boldsymbol{\xi}; \boldsymbol{\beta}^o); \boldsymbol{\beta}^u) - s_{Jt}^D = 0 \end{gathered}$$

Then, we use a definition of δ_j to obtain ξ_j, namely, $\xi_j = \delta_j - \boldsymbol{X}_j \beta^o$. Finally, we use an appropriate set of instruments, $\boldsymbol{Z}_j$, for product j so that we can utilize the moments conditions of $\mathrm{E}[\boldsymbol{Z}' \boldsymbol{\xi}(\boldsymbol{\beta}^u, \boldsymbol{\beta}^o)]$. More precisely, we minimize a following GMM objective function:

$$\hat{\theta} = \operatorname*{argmin}_{\theta} \boldsymbol{\xi}(\boldsymbol{\theta})' \boldsymbol{Z} \Phi^{-1} \boldsymbol{Z}' \boldsymbol{\xi}(\boldsymbol{\theta}),$$

where $\theta = (\boldsymbol{\beta}^u, \boldsymbol{\beta}^o)$ and Φ is a consistent estimate of $\mathrm{E}[Z'\xi\xi Z]$. For instruments, we use a set of instruments suggested by Berry, Levinsohn and Pakes (1995).[10]

[10]We assume that every characteristics is predetermined.

4.2 Construction of Important Variables

Rate of Return In our study, we specify t as year. Even though we observe monthly-level returns and estimated assets for more than half of hedge funds, we sometime observe quarterly- or annual-level returns and estimated assets for some hedge funds. In order to utilize all hedge funds' information, we aggregate monthly- or quarterly-level data into annual-level data. In particular, when we aggregate returns, we use the following standard formula to obtain annual-level return from monthly-level return:

$$r_{j,\text{year}} = \left(\sum_{m=1}^{12} (1 + r_{j,\text{year},m}) \right)^{\frac{1}{12}}.$$

For the annual level volatility, we calculate the variances of the monthly returns.

Market Share and Outside Option As Berry, Levinsohn and Pakes (1995) and Nevo (2001) pointed out, the definitions of outside options and the market share are crucial for correctly estimating our model. In our study, the market should include that from the investors' point of view. Therefore, in our study, we follow Massa (2003) where he uses "*Flow of Funds Accounts of the United States, Annual Flows and Outstandings*," issued by the *Board of the Governors of the Federal Reserve Bank*. Using this information implies that we implicitly assume that the investors are mostly U.S. investors.[11]

5 Estimation Results

In this section, we provide estimation results for two different models: a logit and a random coefficients model. Table 2 shows the estimation results where we use 'Maximum Leverage' as the funds' leverage information, while Table **??**, which is in Appendix, shows the estimation results where we use 'Average Leverage.' Comparing these two results, we observe similar results. Therefore, we focus on explaining the results with maximum leverage in the following section. In Table 2, the second and the third columns show estimates and standard errors for the logit specification where we do NOT include any investors' heterogeneity, while the fourth and fifth columns show the results for the random coefficients model where we include

[11] Of course, we can also mimic Massa (2003) strategy where he uses 'overall market capitalization' to check the robustness of his results. This should be one of our future tasks.

investors' heterogeneity for leverage usage. We demonstrate the coefficients and the standard errors from the second to the fifth rows.

Returns and Volatility As we expect, the past realizations of the returns affect positively and the volatility affect negatively for investors utility as shown from the second to seventh rows. This results are intuitive; investors derive the utility from the good performance in the past periods, and disutility from the volatile performance. Not surprisingly, the last year's realized volatility is not statistically significant for both specifications. Thus, our estimation results suggest that investors are tolerant for the last years' volatility. We also need to emphasize this part of the results are quite robust for any specifications. Moreover, we also included more higher moments, skewness and kurtosis, for testing the robustness of the results. However, these coefficients are typically not statistically significant.[12]

Year and Strategy Dummies We include dummy variables to absorb year specific and strategy specific effects. As for dummy variables for year specific effect, it is very clear to see that the demand in 2008, when the United States was severely affected by financial crisis caused by Lehman Brothers, is much lower than the demand in 2007, which is the base year. For strategy dummies, some strategies, including Equity Market Neutral and Global Macro, are significantly different from the benchmark 'other strategies', which does not fall into any strategies listed in the table.

Management and Incentive Fees For management fee and incentive fess, both coefficients are negative, which should match our intuition, although these are not statistically significant. We doubt that this insignificance is cause by the lack of the variation in management and incentive fees. Most of the funds set their management and incentive fees as 20% and 2%, respectively.

Leverage For leverage, if we assume that there is no heterogeneity for investors, our model predicts that investors positively valuate leverage, on average. Interestingly, this result has been changed when we include the heterogeneity. In a random coefficients model, investors valuate hedge funds' leverage negatively, on average, but standard deviations for the valua-

[12]The estimation results which include higher moments are available upon requests.

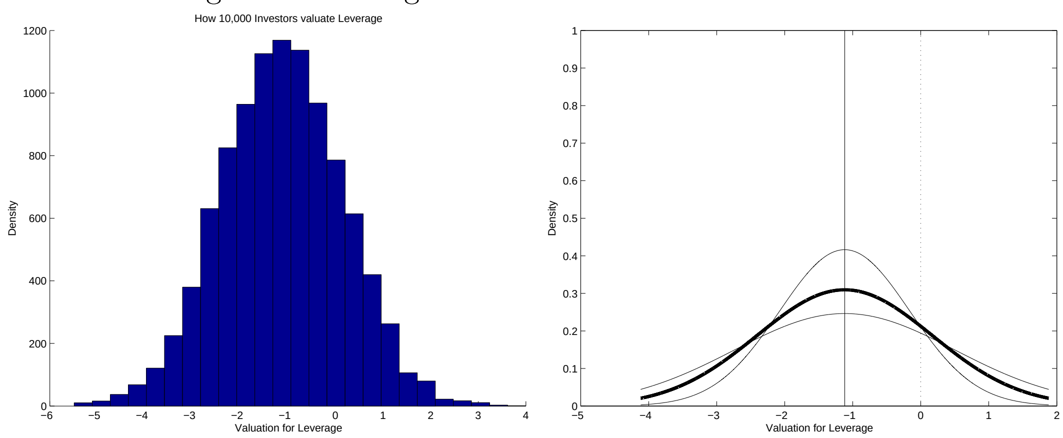
Table 2: Estimation Results 1: Maximum Leverage

	Logit Model		Random Coef. Model	
Variables	Estimates	Std. Err.	Estimates	Std. Err.
Constant	**-14.251**	0.252	**-14.231**	0.465
Rate of Return $t-1$	**14.483**	1.750	**14.474**	2.874
Rate of Return $t-2$	**13.463**	1.845	**13.656**	3.040
Rate of Return $t-3$	**9.622**	1.967	**11.159**	3.099
S.D. Retrun $t-1$	-1.098	1.509	-1.122	2.569
S.D. Retrun $t-2$	**-5.343**	1.710	**-5.456**	2.863
S.D. Retrun $t-3$	**-9.170**	1.779	**-8.561**	2.789
Year Dummy 2008	**-0.297**	0.084	-0.124	0.133
Year Dummy 2009	0.090	0.098	0.208	0.155
Year Dummy 2010	0.041	0.098	0.183	0.157
Year Dummy 2011	0.088	0.107	0.205	0.166
Management Fee	**-0.064**	0.034	-0.071	0.105
Incentive Fee	-0.009	0.006	-0.017	0.012
Maximum Leverage - Mean	**0.202**	0.058	**-1.118**	0.109
Maximum Leverage - S.D.	–	–	**1.289**	0.331
Aevrage Leverage - Mean	–	–	–	–
Average Leverage - S.D.	–	–	–	–
Redemption Freq.	**0.299**	0.036	**0.290**	0.070
Lockup Period	**-0.021**	0.024	-0.023	0.038
Convertible Bond	0.137	0.215	0.217	0.350
Dedicated Short	-0.751	0.619	-0.604	0.455
Emerging Market	0.059	0.198	0.197	0.280
Equity M. Neutral	**-1.018**	0.201	**-0.740**	0.344
Event Driven	-0.049	0.176	0.092	0.253
Fixed Income	**0.567**	0.263	0.616	0.453
Fund of Funds	-0.156	0.177	-0.151	0.257
Global Macro	**1.287**	0.206	**1.099**	0.345
Long/Short Eq. Hedge	**-0.377**	0.159	-0.236	0.224
Managed Features	-0.091	0.183	-0.126	0.294
Multi Strategy	0.318	0.194	0.496	0.283
Option Strategy	-0.056	0.333	-0.012	0.467

tion is also huge and significantly different from zero. Thus, there exist some investors who prefer highly leveraged funds to low leveraged funds.

To see this result more graphically, we simulate 10,000 heterogeneous investors in terms of their evaluation for leverage, and demonstrate their distribution in Figure 6. On the right panel, we demonstrate the distribution including 95% confidence intervals – the flatter one corresponds to the distribution with the highest variance and the skewer one corresponds to the distribution with the lowest variance case.

Figure 6: Leverage Valuation of Simulated Investors



Redemption Restrictions We include two variables which are related to redemption restrictions: (1) redemption frequency, and (2) lockup period. In our study, the unit of redemption frequency is in month (so it is not exactly frequency) and coefficients for this frequency are positive in both specifications, implying that investors appreciate the funds with longer redemption more, compared with the funds with shorter redemption. This finding seems a little bit puzzling, as we expect that investors prefer shorter redemption restrictions. However, our estimation results also indicate that investors prefer the funds with shorter lockup period. Therefore, we suspect that investors might prefer funds with shorter lockup periods, because they are not sure about the quality of the fund. However, once investors observe the quality of the funds, they appreciate longer redemption funds so that the fund manager can take any positions without anxious about the liquidity.

6 Counterfactual Analysis

6.1 Overview of Policy Experiments

Our estimation results show that 20% of investors prefer leverage usage, though 80% of investors do not prefer leverage usage. This observation implies that if governments implemented any regulation where hedge funds cannot use high leverage, depending on their preferences, investors would reallocate their assets from leveraged hedge funds to other hedge funds/financial assets, or still invest to the same hedge funds. Therefore, we conduct a following counterfactual experiment: If the hedge funds were regulated by governments to take lower leverage, how would investors change their behavior? Would investors still continue purchasing lower leveraged funds or switch to other financial assets?

To answer the question, we use the estimated model to predict the counterfactual demand for hedge funds. More precisely, we limit maximum leverage usage to 1000%, 500%, 200%, i.e.,

$$\text{new } \widehat{\text{max leverage}} = \max\{X, \text{max leverage}\},$$

where $X = 1{,}000\%$, 500%, and 200%. This 200% limit comes from the policy proposal by European Commission and the Financial Stability Board (2012). In order to illustrate the regulation effect more clearly and to explore the effectiveness of the regulation, we also set 500% and 1,000%.

Maintaining Assumptions Our current model does not have supply side – we do not model the hedge funds' behavior nor funds' returns and volatility as a function of hedge fund leverage. Therefore, in the following experiments, we assume that (1) the returns and volatility for the hedge funds would *not* change, even though hedge funds could not take high leverage any more, (2) hedge funds would *not* change their characteristics to attract more investors, and (3) there would be *no* entry/exit. We discuss issues caused by these maintaining assumptions later.

6.2 Simulation Results

In this subsection, first, we look at the fund-level effects to understand the investor behavior. Then, in order to derive implications for systemic risk, we demonstrate (1) aggregated-level effects, (2) changes in concentration, (3) changes in asset allocations for risky strategies, and (4) changes in volatility.

6.2.1 Understanding Investors Behavior

First, as we use the micro data, we show micro-level effects when regulations were implemented. Table 3 shows the fund-level changes. In this table, through the first to the third column show Fund ID, leverage ratio, and equity size, through the fourth to the sixth column show changes in equity for 1000%, 500%, and 200% cases, through the seventh to the ninth column show changes in assets for 1000%, 500%, and 200% cases.

Table 3: Regulation Effects by Individual Funds

	Leverage	Asset	Changes in Assets			Changes in Leveraged Assets		
Fund ID	Ratio	Size	1000%	500%	200%	1000%	500%	200%
2327	80	30.01	-29.96	-30.00	-30.00	-2400.08	-2400.53	-2400.56
2568	40	293.90	-289.68	-293.17	-293.68	-11713.77	-11752.37	-11755.55
35138	20	97.44	-85.25	-95.35	-96.80	-1826.97	-1938.41	-1947.60
751	12	223.99	-92.12	-201.33	-217.02	-1369.14	-2574.56	-2673.94
1479	12	840.27	-320.40	-750.93	-812.80	-4716.49	-9468.48	-9860.23
3168	10	1000.00	1.42	-827.91	-947.09	14.22	-9139.55	-9894.17
1201	9	33.86	0.05	-26.00	-31.44	0.42	-265.46	-299.90
5039	9	5792.83	7.95	-4449.00	-5379.64	71.58	-45416.36	-51309.11
43418	8	667.82	0.87	-453.47	-601.91	6.99	-4270.83	-5210.74
37320	7	9887.47	12.07	-5367.38	-8497.68	84.49	-46611.82	-66432.67
43520	7	133.00	0.16	-72.20	-114.31	1.14	-626.99	-893.61
1411	6	69.81	0.08	-22.92	-55.40	0.46	-184.42	-390.04
1994	6	637.69	0.70	-209.37	-505.99	4.21	-1684.52	-3562.72
35348	6	1020.00	1.12	-334.89	-809.35	6.74	-2694.45	-5698.70
34259	2	366.63	0.06	1.11	1.95	0.12	2.23	3.90
35561	2	51.37	0.01	0.16	0.27	0.02	0.31	0.55
75857	1	510.90	0.01	0.16	0.29	0.01	0.16	0.29
76639	1	11.00	0.00	0.00	0.01	0.00	0.00	0.01

Note: The unit for the numbers in fourth through ninth column is $millions.

Under 1,000% regulation, those funds that use more than 1,000% leverage would significantly loose their investors. For example, Funds 2327 and 2568 would loose their shares almost completely. Interestingly, at the same time, Funds 5039 and 37320 would increase their asset sizes, because investors who originally purchased highly leveraged funds (such as 2327, 2568, and 35138) would shift their investment to these relatively high leveraged funds. In other words, these Funds 5039 and 37320 can be seen as good substitutes for Funds 2327, 2568, and 35138, under 1,000% regulation.

Moreover, under 500% regulation, we can observe the same effect, though now more funds that use high leverage ratio would suffer from this regulation. However, those fund that use about 600% would not face so serious decrease of the investment, say 30% on average, compared to the funds that use more than 1,000% that would completely lost their shares. This difference can be explained by the fact that investors who purchased really high leveraged funds is mostly due to the leverage usage. Under 200%, these aforementioned patterns are strengthened with more shift to lower leveraged funds.

6.2.2 Implications for Systemic Risk

In the previous subsection, we understand the investors' behavior under counterfactual scenarios. Now, having this understanding of investors' behavior, we discuss and derive implications for systemic risk.

Macro Measurement: Aggregate-Level Changes Table 4 gives an overview of macro-level regulation effect. In the first two rows under the label of data show the fraction of assets under hedge fund industry and other financial markets (outside options). In the third and fourth, we show the fraction of assets under hedge fund industry and other financial markets under 1,000% regulation, and so on.

According to Table 4, for example, hedge funds industry collected 0.46% of assets and other financial market such as mutual funds and saving collected the rest of 99.54% in 2007.[13] As the next two rows which show the results under 1000% regulation, we can see there is almost no effect, as only 1% of hedge funds use more than 1000% of leverage. However, as the regulation getting tighter, the assets would shift from the hedge fund industry to other financial products, as hedge funds would not be attractive any more for those investors who appreciate leverage usage.

[13] This number for hedge fund industry seems to be small, because we only use the funds located in the U.S. and U.S. dollar funds that reported monthly returns and estimated assets. Also, notice that Lipper TASS database covers approximately 30% of hedge funds. Therefore, if we could include all hedge funds in the world, the number should be much bigger.

Table 4: Simulation Results: Overview

	2007	2008	2009	2010	2011
Data					
In Hedge Funds	0.46%	0.48%	0.48%	0.39%	0.33%
Outside	99.54%	99.52%	99.52%	99.61%	99.67%
1000% Regulation					
In Hedge Funds	0.46%	0.48%	0.48%	0.39%	0.33%
Outside	99.54%	99.52%	99.52%	99.61%	99.67%
500% Regulation					
In Hedge Funds	0.43%	0.46%	0.47%	0.38%	0.32%
Outside	99.57%	99.54%	99.53%	99.62%	99.68%
200% Regulation					
In Hedge Funds	0.40%	0.45%	0.45%	0.36%	0.30%
Outside	99.60%	99.55%	99.55%	99.64%	99.70%

In order to show this result more graphically, we pick up the year 2007 and demonstrate the change in total assets under management in the hedge industry in Figure 7. If there is no regulation, roughly the asset under management in this industry is about 240.9. However, if the government put 1,000% cap, about only 1% of hedge funds were affected by this regulation and the total assets under management would not change dramatically, as in one at the right end. If the government put 500% cap, about 5% of hedge funds needed to lower their leverage and the total assets amount would be 224.4, implying the total assets would be decreased by 6.8%. Moreover, If the government put 200% cap, about 11.1% of hedge funds needed to lower their leverage and the total assets amount would be 221.0, implying the total assets would be decreased by 8.3%.

Micro Measurement 1: Changes in Concentration As we describe in Section 2, one important factor which affect systemic risk is concentration. Therefore, after the simulation, we sort the hedge funds by its asset size and plot the cumulative assets distribution again as in Figure 8. The right and left panel of Figure 8 demonstrate the assets size concentration without and with multiplying by leverage, respectively.

As the left panel of Figure 8 shows, the relative size asset size concentration would not change, as there are not many funds that are affected by the regulation. Interestingly, however, the right panel of Figure 8, which describe the cumulative asset distribution after

Figure 7: Change in Total Asset Holding by Hedge Fund Industry

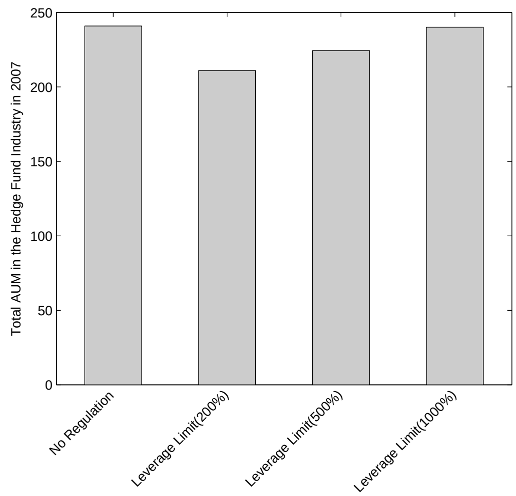
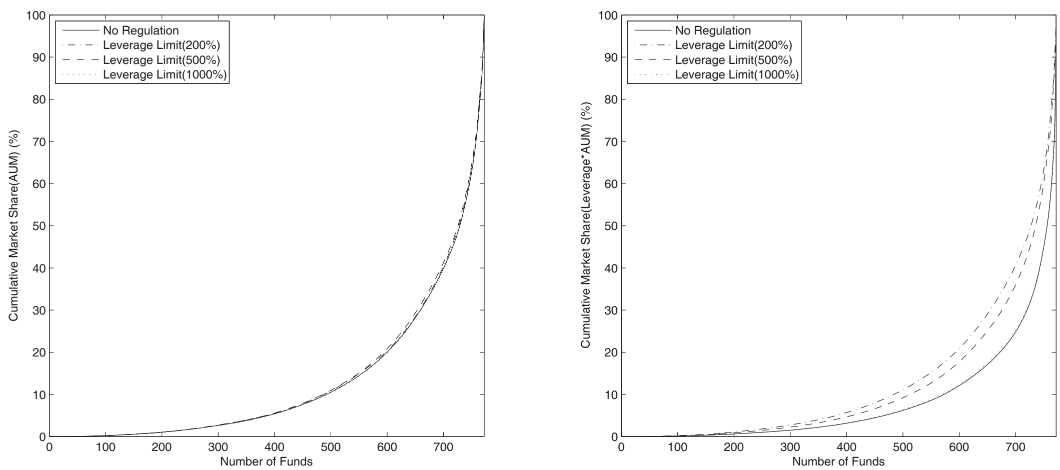


Figure 8: Market Concentration without/with Multiplying Leverage



multiplying by the leverage, shows much larger changes compared to the right panel. This result implies that the asset distribution is much smoother than before. The reason why we have these results as follow: If the government regulated the hedge funds' leverage, some investors who valuate hedge funds' leverage positively would lose their interest for this industry. Among them, some investors might still invest to other hedge funds, but most of them would be likely to shift to other financial products. On the other hand, most of investors who do not prefer high leveraged funds would start purchasing those regulated funds under regulations. These two effects off-set each other and, as a consequence, we do not see any change in cumulative distribution.

However, if we want to take into account the leveraged asset amount, we also need to multiply by the leverage. In the data, hedge fund can use up to 8,000% of leverage, but now these funds can use only 1,000%, 500% or 200%. Therefore, the leveraged-asset distribution should be more smoothed, implying that many funds have similar manageable assets unless they have better fund-specific effect, which is denoted by ξ_j in our model.

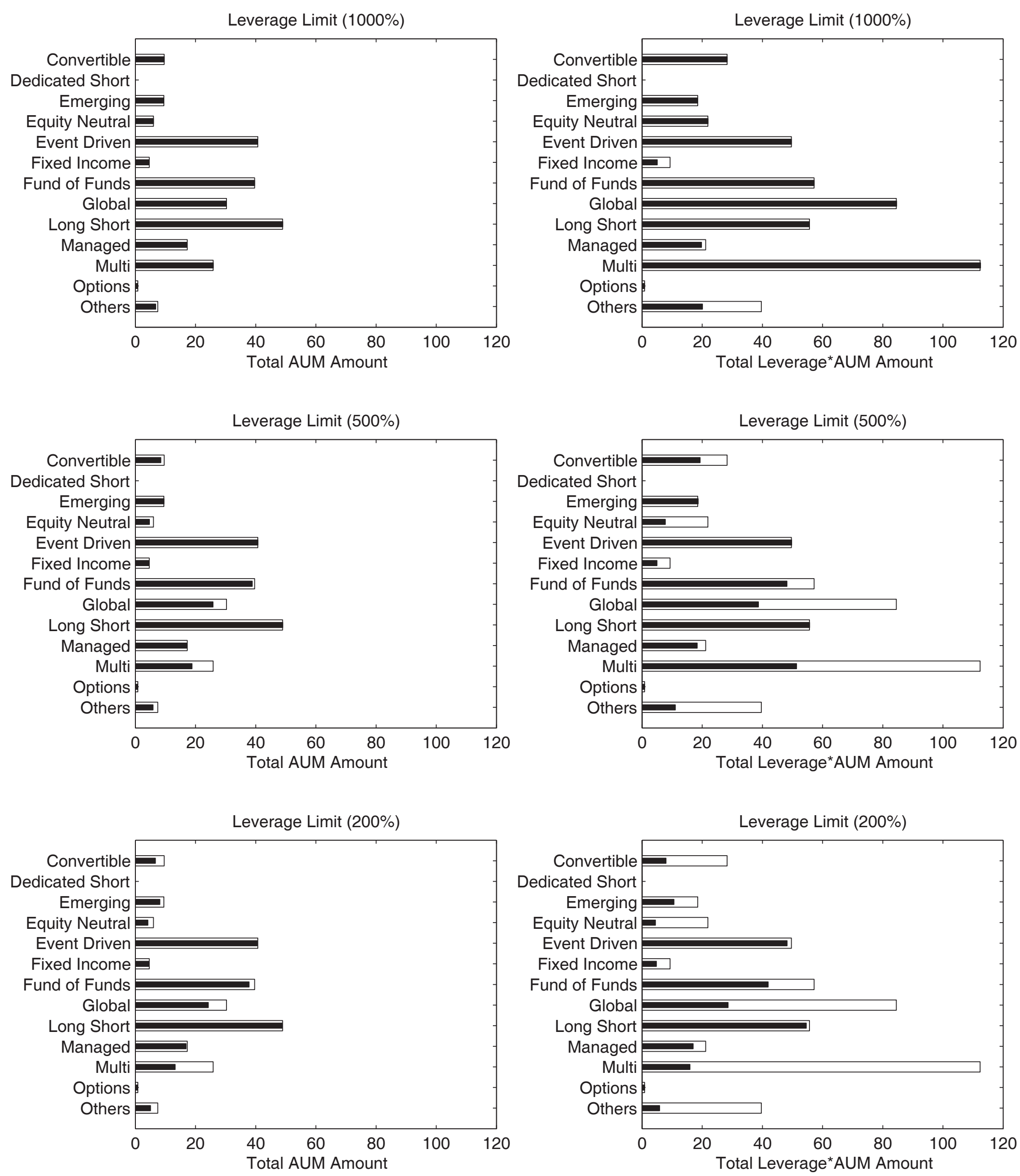
Micro Measurement 2: Changes in Asset Allocations for Risky Strategies Table 6 shows our simulation results by strategy. Every number displayed in this table is percent. For example, the data shows that the asset under hedge funds that use *Convertible Bond* strategy in 2007 is about 0.02%. Under the 200% regulation, however, assets under funds that use the same strategy would decrease by 0.01% and would be 0.01%.

As it is a little bit tough to see effects in Table 6, we also demonstrate our results more graphically in Figure 9. On the left side, top, middle and bottom panels show how much each strategy would collect investments under 1,000%, 500% and 200% regulations, respectively. Similarly, on the right side, top, middle and bottom panels show how much each strategy would manage leveraged assets under 1,000%, 500% and 200% regulations, respectively.

From two figures in the top row, we can, again, see that the impact of 1,000% regulation would not be so large. Even if we take into account the leverage, most strategies would not be affected, except fixed income. However, as regulation get tighter, regulation effects get clearer. For example, funds that use *Global Macro* and *Multi-Strategy* would decrease their asset under management significantly. Moreover, if we take into account their leverage usage, funds that use Convertible, Emerging Market, Equity Neutral, Fixed Income, Global Macro, and Multi-Strategy would significantly decrease their shares. As pointed out in Section 2, we define Fixed Income, Global Macro and Multi-Strategy as risky strategies and it is clearly these strategies would loose their shares, implying that systemic risk would be reduced significantly by 500% or 200% regulation.

Micro Measurement 3: Changes in Volatility Volatility in hedge fund industry is also important factor. Funds with high return volatility are likely to go bankrupt than the

Figure 9: Regulation Effects by Strategy



funds with low volatility. Figure 10 shows how asset reallocation affect investors choice of funds. The horizontal axes show the volatility and AUM size. The vertical axis shows the frequency. We can observe that investors decrease asset allocations to hedge funds with high

Table 5: Total Industry Volatility Change

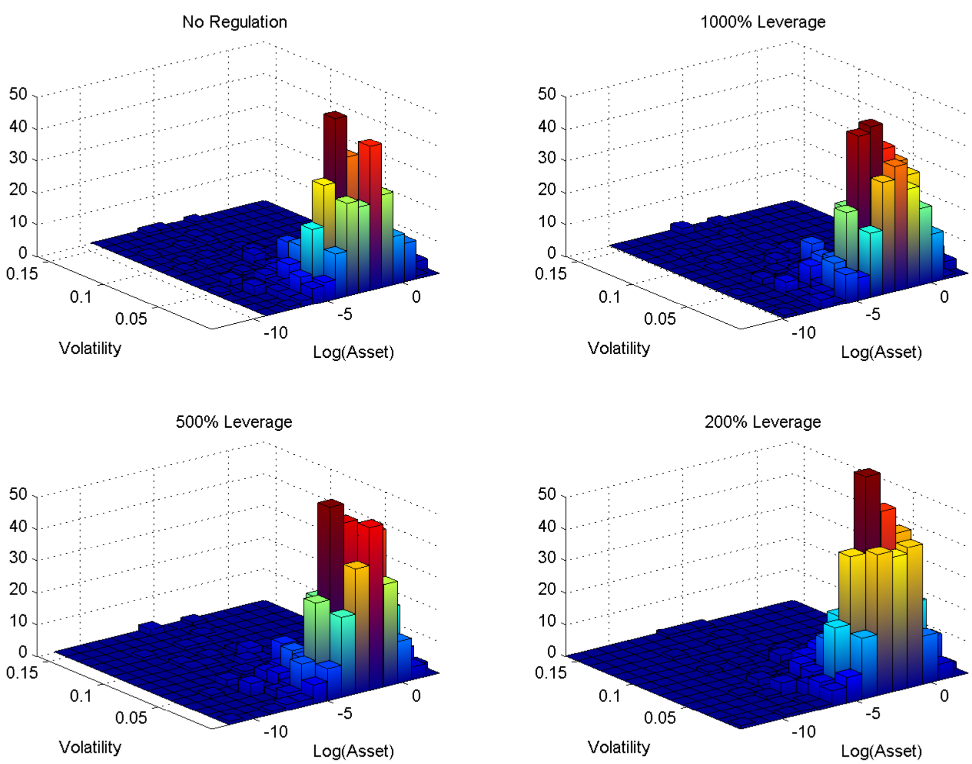
	Data	Simulation		
	(No Regulation)	1000%	500%	200%
Total Industry Volatility	4.74	4.73	4.48	4.23
Change	–	-0.15%	-5.43%	-10.61%

return volatility. We also total industry volatility with the following equation.

$$\text{Total Industry Volatility} = \sum_{j=1}^{J} \text{AUM}_j \times \text{Volatility}_j$$

Table 5 shows the change of the total industry volatility. We observe that the volatility decrease about 10% for the case of 200% leverage cap.

Figure 10: Regulation Effects by Volatility



As a consequence of our analysis for examining three systemic risk factors as well as macro-level effect, we conclude that regulations would lead to lower demand for hedge fund industry, in particular, highly leveraged funds and risk strategies, which in turn, would reduce systemic risk.

6.3 Some Potential Problems

Even though our simulation results show that the demand for hedge funds would decrease as a consequence of leverage regulation. However, there are a couple of concerns to our methodology. Therefore, in this subsection, we summarize these potential problems in evaluating such a counterfactual policy.

Hedge Funds' Behavior In our estimation, hedge funds are not explicitly modeled, and thus, our results cannot take into account the change in behavior of the hedge funds. For example, as a result of the implementation of leverage regulation, some hedge funds might exit from the market or change their other characteristics such as redemption period or incentive fee. In such cases, the demand structure would be changed, corresponding to hedge funds' behaviors – so we cannot have such equilibrium effects.

Leverage and Performance Moreover, our model implicitly assumes that hedge funds' performance would not be changed after the regulation. It is, however, possible that performance would be changed - in particular, we expect that the performance would be worse, because hedge funds cannot take high leverage position any more. Then, observing lower performance, investors would shift their assets from a hedge fund industry to other financial assets. Therefore, our assumption of having the constant performance before and after the regulation might cause some problems.[14]

[14] We will take into account this effect in the future revision.

Table 6: Regulation Effects by Strategy

	Data					1000% Regulation					500% Regulation					200% Regulation				
Strategy	2007	2008	2009	2010	2011	2007	2008	2009	2010	2011	2007	2008	2009	2010	2011	2007	2008	2009	2010	2011
Convertible Bond	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.01
Dedicated Short	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emerging Market	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01
Equity M. Neutral	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Event Driven	0.08	0.08	0.10	0.03	0.03	0.08	0.08	0.10	0.03	0.03	0.08	0.08	0.10	0.03	0.03	0.08	0.08	0.10	0.03	0.03
Fixed Income	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00
Fund of Funds	0.08	0.08	0.07	0.05	0.04	0.08	0.08	0.07	0.05	0.04	0.07	0.07	0.07	0.05	0.04	0.07	0.07	0.07	0.05	0.04
Global Macro	0.06	0.08	0.08	0.10	0.11	0.06	0.08	0.08	0.10	0.11	0.05	0.07	0.08	0.09	0.10	0.05	0.07	0.07	0.09	0.09
Long/Short Eq. Hedge	0.09	0.09	0.09	0.07	0.05	0.09	0.09	0.09	0.07	0.05	0.09	0.09	0.09	0.07	0.05	0.09	0.09	0.09	0.07	0.04
Managed Features	0.03	0.05	0.05	0.04	0.02	0.03	0.05	0.05	0.04	0.02	0.03	0.05	0.05	0.04	0.02	0.03	0.05	0.05	0.04	0.02
Multi Strategy	0.05	0.05	0.04	0.03	0.03	0.05	0.05	0.04	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Option Strategy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other Strategies	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.02	0.02
Outside Options	99.54	99.52	99.52	99.61	99.67	99.54	99.52	99.52	99.61	99.67	99.57	99.54	99.53	99.62	99.68	99.60	99.55	99.55	99.64	99.70

7 Conclusion

This paper estimates investors' hedge fund demand using a framework of estimating differentiated product demand and assesses effects of regulations under policy discussion which aims to reduce systemic risk. Our estimation results show that 20% of investors prefer leveraged funds, while the rest do not. Using the estimated model, we then ask the question of what would happen if governments regulated hedge funds leverage, as suggested by the Financial Stability Board in 2012. Our policy simulations demonstrate that the restriction of leverage would significantly decrease demand for hedge funds, in particular, for highly leveraged funds. Our findings, therefore, suggest that the proposed leverage regulation for hedge funds would reduce systemic risk.

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