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 the effect of regulation being considered by policymakers that aims to enhance financial stability. Using data on fund-level characteristics, we estimate a hedge fund demand that takes into account investors' heterogeneous tastes for using leverage. Our estimation results demonstrate that 20% of investors positively evaluate using leverage. We then conduct a policy simulation in which 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.

Keywords: hedge funds, demand estimation, leverage regulation, systemic risk

JEL Classification: G38, G23, L52

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1 Introduction

After the collapse of several large hedge funds, such as Long-Term Capital Management (LTCM) and Amaranth Advisors, the hedge fund industry has drawn global attention. A central concern for policy makers regarding the hedge fund industry is systemic risk: the failure of one large hedge fund may affect not only its investors but also trading counterparties and creditors, including large financial institutions. As a consequence, this might trigger significant turmoil in financial markets. To prevent a wider collapse, for example, the Federal Reserve Bank of New York organized a bailout of $3.6 billion for LTCM. These historical events led to discussions on tighter regulations on hedge funds, and in 2012 the Financial Stability Board proposed a regulation on the use of leverage.

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

This paper empirically studies such a trade-off between systemic risk and efficiency of financial markets through hedge fund regulations. In particular, the paper attempts to quantify the impact of the proposed regulation to cap the use of leverage on investor behavior and to derive its implications for systemic risk. To answer these questions, we exploit a structural demand estimation technique, a recent development in the industrial organization literature, to recover investor demand for hedge funds and simulate the effects of hypothetical regulations. The methodology enables us to recover investor preference on hedge fund characteristics from market shares. Investors may or may not prefer the leverage usage with preference depending on each investor. Also, the method allows us to predict how investors reallocate their portfolio on hedge fund products under the new regulations. Under these new directives, investors would not be attracted by less leveraged hedge fund products. Or they would start purchasing hedge fund products of different strategies. Investors' choices determine the hedge fund industry features and would change potential systemic risk factors. The demand estimation technique facilitates quantification of the change.

In order to simulate investor behavior under the hypothetical scenario, we estimate a model of investors' demand for hedge funds. In the Lipper TASS hedge fund data, we can observe each hedge funds' characteristics, as well as the amount of 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 used in the finance literature: a seminal work by Massa (2003) examines the demand for mutual funds and analyzes the industry structure.[1] Our current estimation results suggest that about 20% of investors prefer to invest in leveraged funds, while the remaining of investors prefer minimally leveraged funds.

Using the estimated model, we conduct a counterfactual simulation in which the government regulates hedge fund leverage. More precisely, we limit the maximum use of leverage to be equal to 1,000%, 500%, and 200%. Our simulation results suggest that the demand for hedge funds would decrease by about 10% in the 200% cap case. In particular, the demand for highly leveraged hedge funds would drop sharply. The regulation would decrease systemic risk via following three channels: (1) highly leveraged funds would significantly lose significant demand and the distribution of fund portfolio size would be more equal than before, (2) asset allocations would be decreased to some risky strategies hedge funds that are more likely to go bankrupt with large losses, and (3) total industry return volatility would decrease. Thus, we conclude that the proposed regulation of leverage regulation would significantly reduce systemic risk.

Hedge funds and their associated risks are broadly discussed in the existing literature. For example, Aragon and Strahan (2012) show that the shortage of traders' funding liquidity decreased market liquidity in the bankruptcy of Lehman Brothers. Dudley and Nimalendran (2012) also find that investors will suddenly 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 the 2007-2009 financial crisis due to redemption and margin calls. On the other hand, it has also been reported that the hedge fund industry has vulnerable structures. Boyson et al. (2010) study contagion among worst returns in the hedge fund industry. Gupta and Liang (2005) discuss hedge funds' undercapitalization, while Ang, Gorovyy and van Inwegen (2011) study hedge

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

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. Section 3 presents the model and Section 4 depicts the estimation procedure. The estimation results are presented in Section 5. The effects of change in regulation is then 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 representatives of the hedge fund universe. Compared to other databases, the Lipper TASS database includes detailed fund characteristics such as use of leverage, redemption restrictions, trading instruments, and so on. Therefore, this is one of the most suitable databases for conducting the demand analysis. To avoid issues with survivor bias, we use both live and graveyard funds. Also, we include the fund of hedge funds for that is 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 include the hedge funds whose domicile currency is the US dollar to analyze investors behaviors in the US. Then, we exclude hedge funds that do not report asset size, rate of return and fund characteristics. We assume that the alternative investment option to hedge fund investment is the total financial wealth not invested in hedge funds in the sample, taken from the Flow of Funds Accounts of the United States, Annual Flows and Outstandings issued by the Board of Governors of the Federal Reserve System, as Gavazza (2011) does. Table 1 depicts sample statistics. In the rest of this subsection, we describe in more detail 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 the use of leverage. The use of leverage in the Lipper TASS data is defined as the portfolio/equity ratio. If this number is equal to one (100%), then the portfolio size is equal to the size of assets under management (hereafter AUM), which is the amount of money for which the hedge fund has the right to

Table 1: Summary Statistics

	Mean	Std. Dev	Min	Max
Rate of Return	0.0026	0.027	-0.783	0.104
S.D. of Rate of Return	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

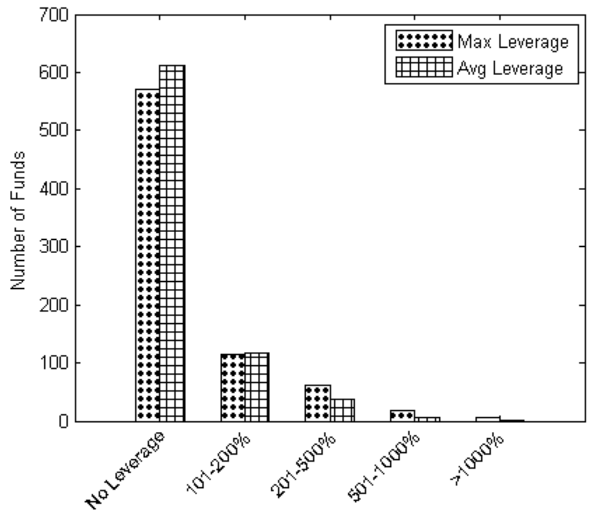
claim a management and/or an incentive fee. If this number exceeds one, then the hedge fund manages more assets than what it originally had by using derivatives or borrowing money from other financial institutions and collateralizing some of the funds' assets.

Figure 1 shows the use of leverage in ordinary times, 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 highly leveraged hedge funds fail, creditors such as large banks or other financial counterparties would take a large loss and be destabilized. Therefore, highly leveraged funds can be considered a 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 the direction of markets.

[2]This statistic on leverage usage coincides with an internal survey on European hedge funds by the European Central Bank (2005).

Figure 1: Leverage Usage

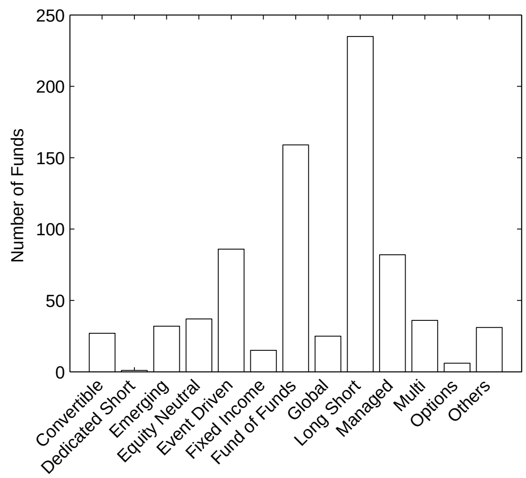


This category includes strategies called *long/short equity*, *global macro*, *managed futures*, *dedicated short bias*, and so on. The main difference between traditional funds and hedge funds is that hedge funds use short positions and exposure to derivatives. Third, *event driven* hedge funds aim to make profits using events such as mergers, restructuring and the failure of firms. Furthermore, *multi-strategy* funds use several other strategies and *funds 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 sizes are smaller than those of funds that use other strategies, on average.

2.2 Measurements of Systemic Risk

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

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



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 the Herfindahl-Hirschman Curve, inspired by Herfindahl-Hirschman Index(HHI) which is commonly used in the industrial organization literature.

The left and right panels in Figure 4 show the market concentration with assets and assets multiplied by leverage in the industry, respectively.[3] We observe that both curves skew downwards, implying that the top percentage of funds manage a large fraction of the assets and 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 these strategies are more likely to lead the fund to go bankrupt with large losses. As pointed out by Ferguson and Laster (2007), *Global Macro*, *Fixed Income Arbitrage* and *Multi-Strategy* were the main strategies behind past large-scale

[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 in ascending order. If we observe a 45-degree straight line in the graph, it implies that every hedge fund has exactly the same amount of assets.

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

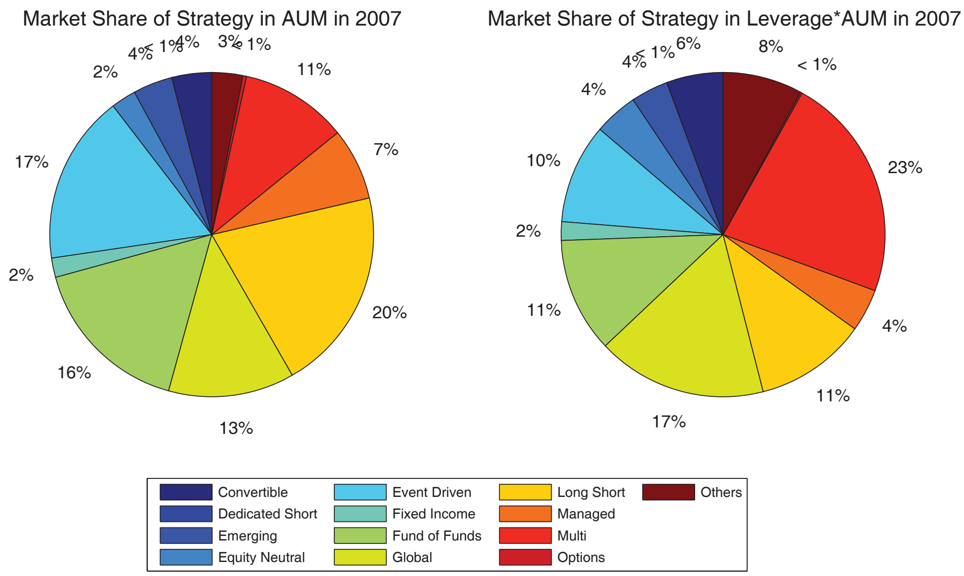
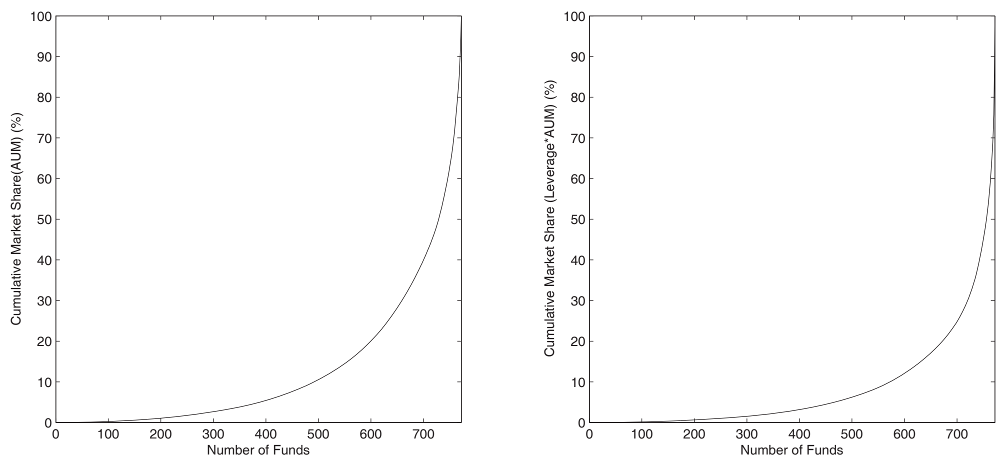


Figure 4: Concentration of Hedge Fund Assets

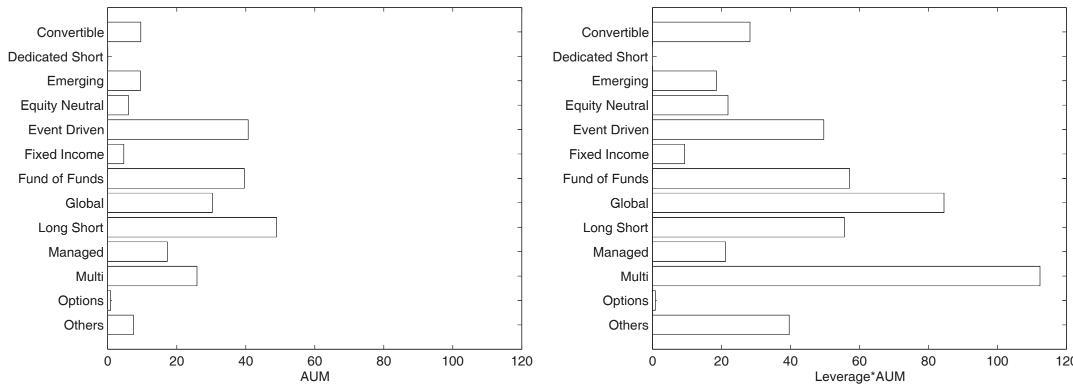


Note: The left panel shows assets under management, while the right panel shows assets under management multiplied by leverage. We use the sample in 2007 and the number of existing funds in 2007 is 772.

failures, accounting for 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 the shares of each strategy in terms of assets and leveraged assets in 2007. Risky hedge funds such as global macro, fixed income arbitrage and multi-strategy account

Figure 5: Asset Allocations by Strategy in 2007



for 21% of industry assets under management, though they account for much higher shares in terms of leveraged assets due to the high use of leverage.

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

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

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

3 Model

3.1 Overview of the Model

Our final goal to examine the 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 regulations that have not been implemented yet, implying that it is difficult to directly use standard regression analysis.[4] Therefore, we use a structural

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

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

approach to tackle this problem, i.e., we recover the investors' indirect utility function by modeling the investors' hedge fund choice problem, and then simulate how their hedge fund choice would be changed under regulations.[5]

More precisely, since the data include yearly aggregate-level market share and fund-level characteristics, we use a methodology developed by Berry (1994) and Berry, Levinsohn and Pakes (1995) in which 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, use of leverage, and so on. Then, we assume that each investor derives utility from these characteristics of the hedge funds and invest in the fund that gives the highest utility. Since we observe multiple years of market shares, we have some variation in the investors' choice set. Intuitively, observing the relatively higher market share for some funds, we can infer how investors evaluate 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 the industrial organization literature, as well as in recent studies in finance, and has become popular in the last decade. For instance, Massa (2003) uses this technique to recover investors' utility from mutual fund choice, and Schroth (2006) studies firms' choice of an underwriter.[7]

3.2 Investors' Behavior

Specifically, in the hedge fund industry, we assume investor utility as follows. Let j denote each hedge fund. A vector of characteristics for each fund j is denoted by $\boldsymbol{X}_{jt}$ such as

From this regression, we can infer is (marginal) effect of the 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 change in asset size). However, our intuition tells us that this is not the case, because some funds might be a substitute for fund j and those funds are (negatively) affected by regulations; thus, some investors would invest in 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.

[6]Of course, if we had investor-level portfolio data, we could have used different approach. However, such data are rarely available and we only have macro-level market share data for this study. Importantly, one of the prominent features of Berry, Levinsohn and Pakes (1995) methodology is that we can still recover the demand function from the data on market share and product characteristics, without having such investor-level portfolio data.

[7]There are more studies using similar techniques.

each fund's strategy, redemption notification period, incentive and management fees, past performances and so on. We assume that investor i get utility from a return $r_{j,t}$ at time t under the functional form of u_{ij}.[8]

$$u_{ijt} \quad = \quad u_{ij}(r_{jt}) \tag{1}$$

The $r_{j,t}$ is a function of investing technologies and tactics depending on fund characteristics and strategies $\boldsymbol{X}_{jt}$,and a hedge-fund-specific unobserved term ξ_j.

$$r_{jt} = r_{jt}(\boldsymbol{X}_{jt}, \xi_j) \tag{2}$$

Investor i has his/her own valuation for hedge fund characteristics which derive a future output, and also has his/her "appreciation" for those characteristics. We assume that this indirect utility function is

$$u_{ij} = u_{ij}(r_{jt}(\boldsymbol{X}_{jt}, \xi_j)) = \boldsymbol{X}_{jt}\boldsymbol{\beta}_i + \xi_j + \varepsilon_{ijt} \tag{3}$$

where ε_{ijt} denotes a random utility shock.

In this model, we assume that investors evaluate hedge fund j from both past performances and fund characteristics. This approach is supported by the empirical observation that hedge fund returns are highly volatile and difficult to predict a future return only from past performances, and the hedge fund with the highest past performances does not necessarily take all of the industry investment. For example, the use of leverage contains information on future volatility distribution and riskiness in crisis, which are not included in past performance information. Therefore the leverage indirectly affects investor utility. Past studies on funds choice, such as Massa (2003), Hortacsu and Syverson (2004) and Gavazza (2011), also derive similar indirect utility functions which is a linear function of observable funds characteristics and past performances, implicitly or explicitly. Furthermore, reduced form researches on fund market shares, such as Khorana and Servaes (2012), implicitly assume that demand of funds depends not only on past performances, but also on fund characteristics.

We assume each investor has a different valuation on hedge fund characteristics, and

[8] $r_{j,t}$ may be a random draw from specific probability distribution.

$\boldsymbol{\beta}_i = [\beta_{i,1}, \beta_{i,2}, \cdots, \beta_{i,M}]'$ represents an $m-$dimensional heterogeneous coefficients vector for hedge fund characteristics. This is because each investor has a different asset portfolio and has different utility to diversify their positions. Also, they have different beliefs regarding how hedge fund characteristics affect on future outputs. These elements may generate leverage lovers and haters. Notice that except for ξ_j and ε_{ijt}, the indirect utility depends on observable hedge fund characteristics; and except for ε_{ijt} the indirect utility only depends on hedge fund brand j and time t.

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

$$\beta_{i,m} \quad = \quad \beta^o_m + \beta^u_m \nu_{i,m}, \quad \text{where } \nu_{i,m} \sim N(0,1) \tag{4}$$

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.[9] As we saw in Section 2, the data suggest that non-negligible fraction of hedge funds use leverage and there is demand for these funds, implying that some investors positively value the use of leverage. Thus, even though investors value one of the characteristics – leverage – negatively on average, some people who have a positive shock, $\nu_{i,m}$, can have a positive valuation of that characteristic. Notice that the standard homogeneous coefficients model can be expressed as one of the special cases of this model by assuming $\beta^u_m = 0$ for every characteristic m.

Now, plugging the coefficients vector, equation (4), into the utility function, equation (3), we can rewrite the utility function as

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

where $\boldsymbol{\beta}^o = [\beta^o_1, \cdots, \beta^o_M]'$ and $\boldsymbol{\beta}^u_i = [\beta^u_1\nu_{i,1}, \cdots, \beta^u_M\nu_{i,M}]'$. Define 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 redefine $\boldsymbol{X}_{jt}\boldsymbol{\beta}^u_i$ as the *deviation from the mean*, μ_{ijt}. These expressions enable us to

[9] Alternatively, we can also express equation (4) 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 choose outside options, $j = 0$, we assume that investors will obtain a utility of zero, $\delta_{0t} = 0$, for normalization purposes. 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 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

$$
s_{jt} = \int_{i \in \mathcal{I}} \Pr(d_{i,t} = j | \{\boldsymbol{X}_{kt}, \xi_k\}_{k \in \mathcal{J}_t}, \boldsymbol{\nu}_i) dF(\boldsymbol{\nu}). \tag{5}
$$

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

$$
s_{jt} = \frac{\exp(\delta_{jt})}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt})}, \tag{6}
$$

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 the outside option as

$$
s_{0t} = \frac{1}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt})}. \tag{7}
$$

Using the inversion technique developed by Berry (1994) – dividing both sides of equations (6) and (7), and taking the logarithm – we can obtain the mean utility as

$$\begin{aligned} \log(s_{jt}) - \log(s_{0t}) &= \delta_{jt} \\ &= \boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \xi_{jt}. \end{aligned} \tag{8}$$

where the second equation is derived by the definition of δ_{jt}. Therefore, we can estimate the model with the standard regression technique, assuming ξ_{jt} as residuals. Moreover, for the case of the nested logit model, equation (8) can be rewritten as

$$\log(s_{jt}) - \log(s_{0t}) = \boldsymbol{X}_{jt}\boldsymbol{\beta}^o + \sigma \log(s_{j/g}) + \xi_{jt}, \tag{9}$$

where $s_{j/g}$ denotes the share within the same group.[10] 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 an 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 demonstrated in Section 3, if the model does not include heterogeneity in investors' preference, we can estimate the model using a standard regression. However, it is impossible to use this method, if the model includes heterogeneity, as in equation (5). Therefore, we use simulation to obtain the market share:

$$s^S_{jt}(\boldsymbol{X}, \boldsymbol{\delta}) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{l \in \mathcal{J}_t} \exp(\delta_{lt} + \mu_{ilt})}, \tag{10}$$

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

by generating ns times random numbers for $\boldsymbol{\nu}_i$, which enables us to calculate μ_{ijt}. Since we know the market share of each fund, we can estimate the parameter by minimizing the distance between the observed and the 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 this method is intuitive, this minimization is computationally expensive and we commonly use the estimation procedure developed by Berry, Levinsohn and Pakes (1995) and Nevo (2001), in which they use the orthogonality conditions between 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 the unobserved fund manager skill for example. Then, we expect that a good fund manager will yield higher returns, implying that ξ_j will be correlated with the rate of return. In order to take into account such endogeneity, we use an instrumental variables approach. Specifically, simulated share equations (10) 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 use the moments conditions of $\mathrm{E}[\boldsymbol{Z}'\boldsymbol{\xi}(\boldsymbol{\beta}^u, \boldsymbol{\beta}^o)]$. More precisely, we minimize the 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 $\mathrm{E}[Z'\xi\xi Z]$.

4.2 Construction of Important Variables

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

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

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

Market Share and Outside Option As Berry, Levinsohn and Pakes (1995) and Nevo (2001) point out, the definitions of outside option and the market share are crucial for correctly estimating our model. In our study, the market should include the investors' point of view. Therefore, in our study, we follow Massa (2003), who uses the Flow of Funds Accounts of the United States, Annual Flows and Outstandings, issued by the *Board of Governors of the Federal Reserve System*. Using this information is equal to implicitly assuming that investors are mostly from the US. [11]

In this study, we do not specify the outside option explicitly. It may capture whole financial products in the US such as cash, equities, bonds, mutual funds, derivatives and so on. Some of financial products in the category of outside option may have similar characteristics (e.g. leverage and riskiness) to hedge funds. However, these products generally do not use high leverage and are still quite different with respect to redemption restrictions, information disclosure, or openness to public.

It is possible to study the substitutability with other financial products such as mutual funds. However, this paper attempts to examine the substitutability (i) among hedge funds and (ii) between hedge funds and other financial products (an outside option). Therefore, we abstract investors hedge fund choices from other asset allocation of their portfolios.

[11] Of course, we can also mimic Massa (2003)'s strategy where he uses 'overall market capitalization' to check the robustness of his results. This will be reserved for future research.

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 when we use 'maximum leverage' as the funds' leverage information, while Table 7 in the Appendix shows the estimation results when we use 'average leverage.' Comparing these two models, we observe similar results. Therefore, we focus on explaining the results with maximum leverage in the following section. In Table 2, the second and third columns show estimates and standard errors for the logit specification where we do NOT include investors' heterogeneity, while the fourth and fifth columns show the results for the random coefficients model where we include 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 returns positively affect and volatility negatively affect investors' utility, as shown in the second to seventh rows. These results are intuitive; investors derive utility from good past performance, and disutility from volatile performance. Not surprisingly, last year's realized volatility is not statistically significant for both specifications. Thus, our estimation results suggest that investors are tolerant of last year's volatility. We also need to emphasize that this part of the results is quite robust for any specifications. Moreover, we also included 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 effects, it is very clear that demand in 2008 is much lower than demand in 2007, which is the base year.[13] For strategy dummies, some strategies, including equity market neutral and global macro, are significantly different from the benchmark 'other strategies,' which do not fall into any strategies listed in the table.

[12]These estimation results that include higher moments are available on request.

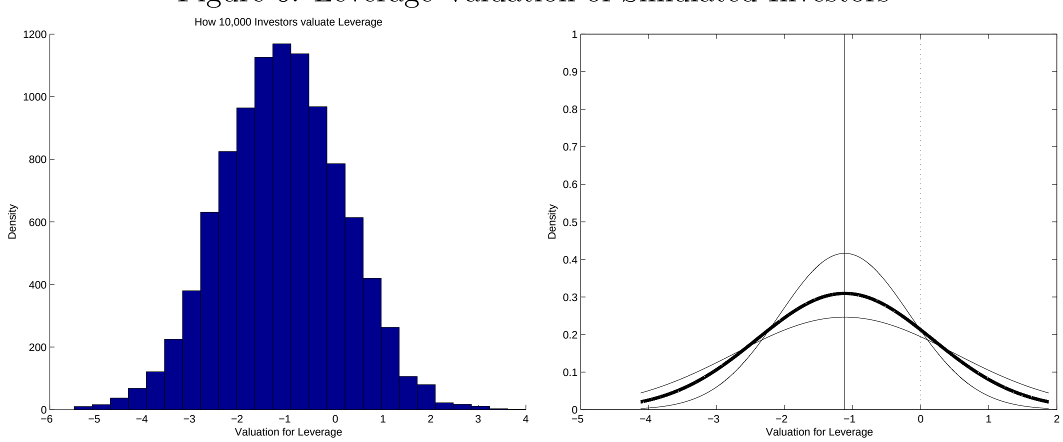
[13]This is because the United States was severely affected by a financial crisis caused by the bankruptcy of the Lehman Brothers in 2008.

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

Leverage For leverage, if we assume that there is no heterogeneity for investors, our model predicts that investors positively value leverage, on average. Interestingly, this result changes when we include heterogeneity. In a random coefficients model, investors value hedge fund leverage negatively, on average, but standard deviations for the valuation are also huge and significantly different from zero. Thus, there exist some investors who prefer highly leveraged funds to minimally leveraged funds.

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

Figure 6: Leverage Valuation of Simulated Investors



Redemption Restrictions We include two variables that are related to redemption restrictions: (1) redemption frequency, and (2) lockup period. In our study, the unit of redemption frequency is a month (so it is not exactly frequent) and the coefficients for this frequency are positive in both specifications, implying that investors more highly value the

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. Return $t-1$	-1.098	1.509	-1.122	2.569
S.D. Return $t-2$	**-5.343**	1.710	**-5.456**	2.863
S.D. Return $t-3$	**-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
Average 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
Strategy Dummy				
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 Futures	-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

funds with longer redemption, compared with the funds with shorter redemption. This finding seems a little bit puzzling, since we expect that investors would prefer shorter redemption restrictions. However, our estimation results also indicate that investors prefer funds with shorter lockup periods. Therefore, we suspect that investors may 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 value longer redemption funds, so that the fund manager can take any position without being anxious about liquidity.

6 Counterfactual Analysis

6.1 Overview of Policy Experiments

Our estimation results show that 20% of investors prefer the use of leverage, though on average most evaluate it negatively. This observation implies that if the government implemented a regulation that prevented hedge funds from using high leverage, depending on their preferences, investors would reallocate their assets from leveraged hedge funds to other hedge funds/financial assets continue to invest in the same hedge funds. Therefore, we conduct the following counterfactual experiment: If hedge funds were regulated by the government to use lower leverage, how would investors change their behavior? Would investors continue to investing in less 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%. The 200% limit comes from the policy proposal by the European Commission. In order to illustrate the effects of regulation more clearly and to explore its effectiveness, we simulate counterfactual demand for 500% and 1,000%.

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

6.2 Simulation Results

In this subsection, we first look at the fund-level effects to understand investor behavior. Then, in order to derive the 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 Investor Behavior

First, since we use micro data, we show micro-level effects when regulations are implemented. Table 3 shows the fund-level changes. In this table, the first through third columns show the fund ID, the leverage ratio, and asset size, while the fourth through the sixth columns show the changes in assets for the 1000%, 500%, and 200% cases respectively. The seventh through ninth columns show the changes in leveraged assets for the respective 1000%, 500%, and 200% cases.

Under 1,000% regulation, those funds that use more than 1,000% leverage would significantly lose their investors. For example, funds 2327 and 2568 would lose their shares almost completely. Interestingly, at the same time, funds 5039 and 37320 would increase their asset size, 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, 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 observe the same effect, though now more funds that use high leverage ratios would suffer under this regulation. However, those funds that use about 600% leverage would not face a serious decrease in investment, say 30% on average, compared to the funds that use more than 1,000% which would completely lose their shares. This difference can be explained by the fact that investors who invested in very high leveraged funds wanted to invest in such funds. Under 200%, these aforementioned patterns

Table 3: Regulation Effects by Individual Fund Level

Fund ID	Leverage Ratio	Asset Size	Changes in Assets 1000%	500%	200%
2327	80	30.01	-29.96	-30.00	-30.00
2568	40	293.90	-289.68	-293.17	-293.68
35138	20	97.44	-85.25	-95.35	-96.80
751	12	223.99	-92.12	-201.33	-217.02
1479	12	840.27	-320.40	-750.93	-812.80
3168	10	1000.00	1.42	-827.91	-947.09
1201	9	33.86	0.05	-26.00	-31.44
5039	9	5792.83	7.95	-4449.00	-5379.64
43418	8	667.82	0.87	-453.47	-601.91
37320	7	9887.47	12.07	-5367.38	-8497.68
43520	7	133.00	0.16	-72.20	-114.31
1411	6	69.81	0.08	-22.92	-55.40
1994	6	637.69	0.70	-209.37	-505.99
35348	6	1020.00	1.12	-334.89	-809.35
34259	2	366.63	0.06	1.11	1.95
35561	2	51.37	0.01	0.16	0.27
75857	1	510.90	0.01	0.16	0.29
76639	1	11.00	0.00	0.00	0.01

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

are strengthened with more shifting to less leveraged funds.

6.2.2 Implications for Systemic Risk

In the previous subsection, we sought to understand 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 the macro-level effects of regulation. The first two rows, labeled as data, show the fraction of assets in the hedge fund industry and other financial markets (outside options). In the third and fourth rows, we show the fraction of assets in the hedge fund industry and other financial markets under 1,000% regulation, and so on.

According to Table 4, for example, in 2007, the hedge funds industry collected 0.46% of assets, and other financial markets such as mutual funds and saving accounts collected

Table 4: Simulation Results: Overview

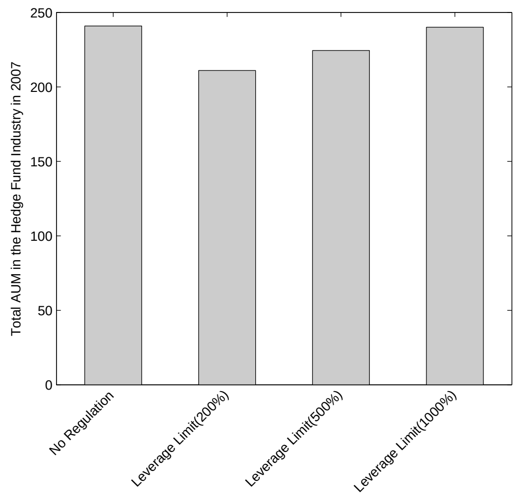
	2007	2008	2009	2010	2011
Data					
In Hedge Funds	0.46%	0.48%	0.48%	0.39%	0.33%
Outside	99.54%	99.52%	99.52%	99.61%	99.67%
1000% Regulation					
In Hedge Funds	0.46%	0.48%	0.48%	0.39%	0.33%
Outside	99.54%	99.52%	99.52%	99.61%	99.67%
500% Regulation					
In Hedge Funds	0.43%	0.46%	0.47%	0.38%	0.32%
Outside	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%

99.54%.[14] The next two rows show the results under 1000% regulation, and we can see there is almost no effect, since only 1% of hedge funds use more than 1000% leverage. However, as regulation gets tighter, the assets shift from the hedge fund industry to other financial products, since hedge funds would no longer attractive for those investors who value the use of leverage.

In order to show this result more graphically, we focus on 2007 and demonstrate the change in total assets under management in the hedge industry in Figure 7. If there is no regulation, the assets under management in this industry are roughly about 240.9 billion dollars. However, if the government imposes a 1,000% cap, only about 1% of hedge funds are affected by this regulation and the total assets under management would not change dramatically, as seen in the bar at the right end. If the government imposes a 500% cap, about 5% of hedge funds need to lower their leverage and the total amount of assets would be 224.4 billion dollars, implying that total assets would decrease by 6.8%. Moreover, the government imposes a 200% cap, about 11.1% of hedge funds need to lower their leverage, and the amount of total assets would be 221.0 billion dollars, implying the total assets would decrease by 8.3%.

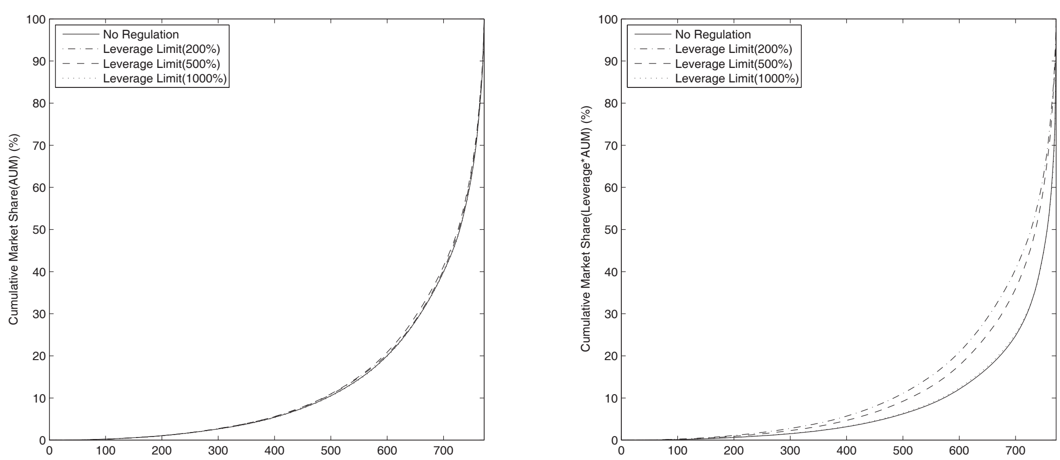
[14] This number for the hedge fund industry seems small, because we only use funds located in the U.S. and U.S. dollar funds that reported monthly returns and estimated assets. Also, notice that the Lipper TASS database covers approximately 30% of hedge funds. Therefore, if we could include all hedge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

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



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

Figure 8: Market Concentration without/with Multiplying Leverage



As the left panel of Figure 8 shows, the relative asset size concentration would not change, since there are not many funds affected by the regulation. Interestingly, however, the right panel of Figure 8, which describes the cumulative asset distribution after multiplying by leverage, shows much larger changes compared to the right panel. This result implies that the asset distribution is much smoother than before. The reason for these results is as follows: If the government regulated the hedge funds' leverage, some investors who value hedge funds' leverage positively would lose interest in this industry. Among them, some investors might continue to invest in other hedge funds, but most of them would likely shift their investments to other financial products. On the other hand, most of the investors who do not prefer high leveraged funds would start purchasing less leveraged regulated funds after the regulation was implemented. These two effects offset each other and, as a consequence, we do not see any change in the 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, a hedge fund 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 smoother, implying that many funds have similar managed assets unless they have better fund-specific effects, 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 a percentage. For example, the data show that, in 2007, the percentage of assets in hedge funds that use a Convertible Bond strategy was about 0.02%. Under the 200% regulation, however, assets in funds that use the same strategy would decrease by 0.01% and would be 0.01%.

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

From the top row of the two figures, we can again see that the impact of 1,000% regulation would not be so large. Even if we take leverage into account, most strategies would not be affected, except for fixed income. However, as regulation gets tighter, regulation effects

Table 5: Change in Total Industry Volatility

	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%

become clearer. For example, funds that use a Global Macro or Multi-Strategy would decrease their assets under management significantly. Moreover, if we take into account their use of leverage, 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 clear that these strategies would lose their shares, implying that systemic risk would be reduced significantly under 500% or 200% regulation.

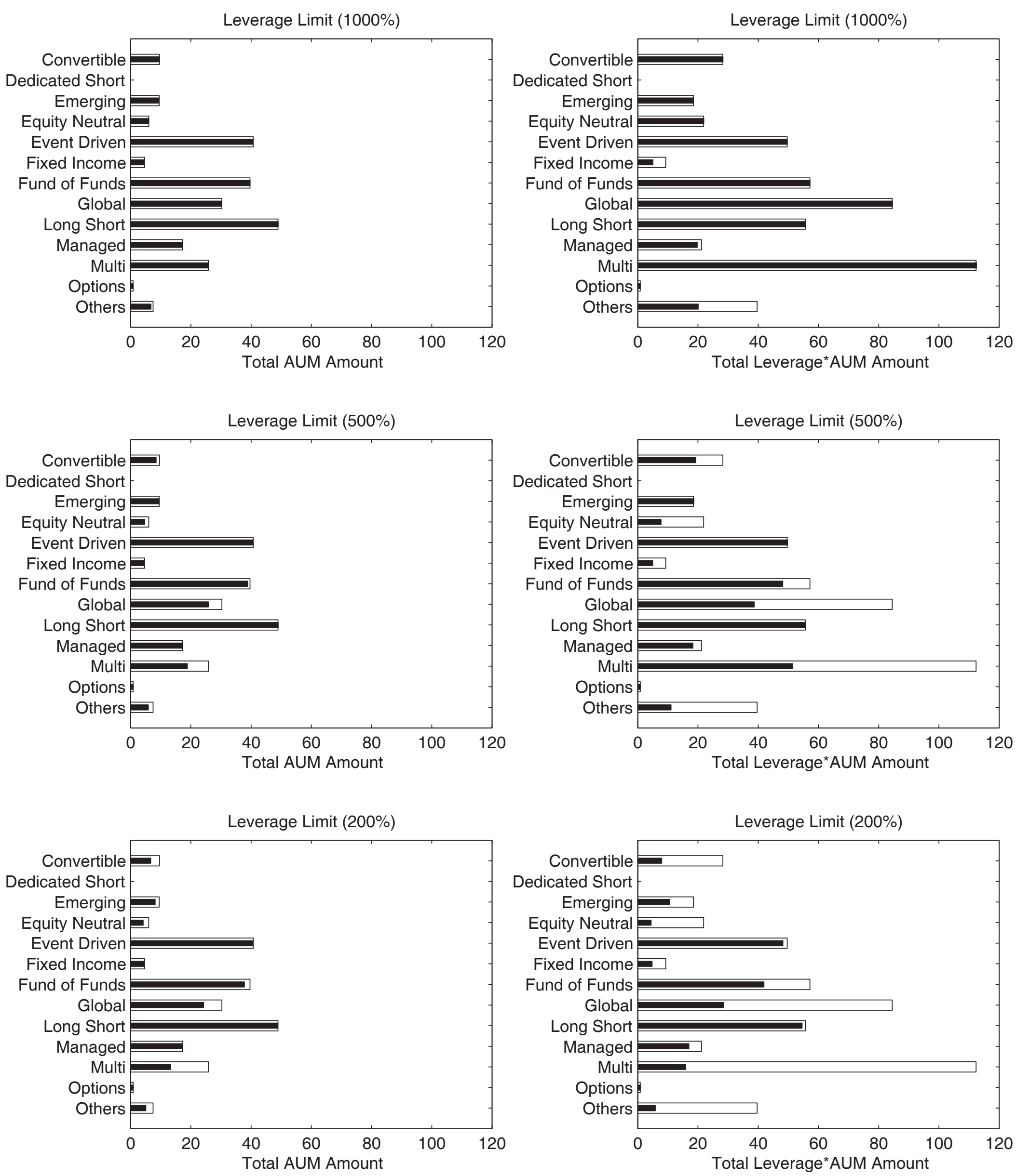
Micro Measurement 3: Changes in Volatility Volatility in the hedge fund industry is also an important factor. Funds with high return volatility are more likely to go bankrupt than the funds with low volatility. Figure 10 shows how asset reallocation affects investors' choice of funds. The horizontal axes show the volatility and asset size. The vertical axis shows the frequency. We can observe that investors decrease asset allocations to hedge funds with high return volatility. We also calculate 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 in total industry volatility. We observe that volatility would decrease about 10% for the case of a 200% leverage cap.

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

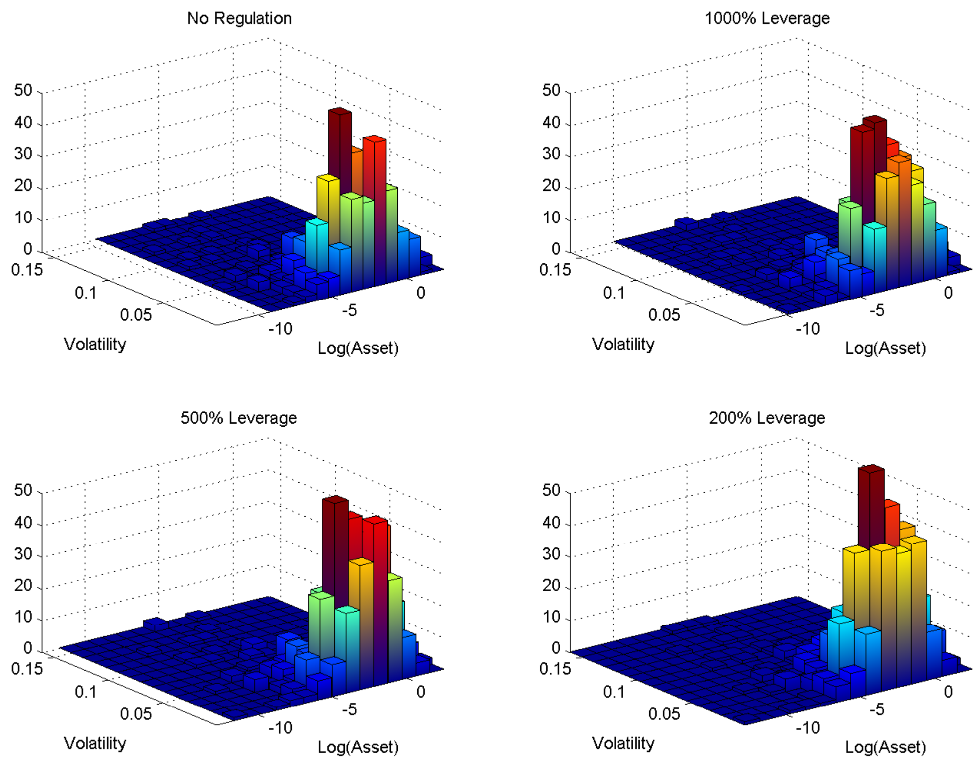
Figure 9: Regulation Effects by Strategy



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, there are a couple of concerns about our methodology.

Figure 10: Regulation Effects by Volatility



Therefore, in this subsection, we summarize these potential problems in evaluating such a counterfactual policy.

Hedge Fund Behaviors In our estimation, hedge funds are not explicitly modeled, and thus, our results cannot take into account their changes in behavior. For example, as a result of the implementation of leverage regulation, some hedge funds might exit from the market, because profits for some of their strategies highly depend on the use of leverage. Also, they might change other characteristics such as redemption periods or incentive fees. Furthermore, hedge funds may purchase riskier assets after the regulations because they can no longer use high leverage. In such cases, the demand structure would be changed, corresponding to hedge funds' behavior; so we cannot have such equilibrium effects.

Leverage and Performance Moreover, our model implicitly assumes that hedge funds' performance would not be changed after regulation. It is, however, possible that performance would be changed; in particular, we expect that performance would be worse because hedge funds can no longer take highly leveraged positions. Then, observing the lower performance, investors would shift their assets from hedge funds to other financial assets. Therefore, our assumption that performance would be constant before and after regulation might cause some problems.[15]

Systemic Measurement To measure systemic risk, we only consider the hedge fund industry structure from the view of investor behavior. However, hedge funds affect financial markets in different ways. Leveraged hedge fund failures induce fire sales of illiquid assets, turmoils in particular markets, destabilization to large commercial banks, and credit crunches in funding markets. Due to data shortage, we cannot consider these factors, but these are also important for systemic risk measurements.

[15] We will take this effect into account in a 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 Futures	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 studies investors' hedge fund choice using a framework estimating differentiated product demand. It further assesses the effects of proposed regulations that aim to reduce systemic risk throughout financial system. 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 the government regulated hedge funds' use of 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 regulation of the use of leverage by hedge funds would reduce systemic risk.

For policy implications, this paper finds that 20% of investors have a "risk appetite." However, if regulators discipline their appetites, there would be significantly less systemic risk: the industry would be less concentrated, the risky strategy proportion of the industry would be reduced, and total industry asset and volatility would decrease. As the leverage limits become tighter, those safer features would be reinforced, because investors would significantly move their assets from large, risky, high leveraged funds to an outside option or to small, safe, less leveraged hedge funds. As a caveat, this paper studies the regulation effects viewed from investor behaviors. Certainly, one interesting direction to continue this line of research would be to study how hedge funds would change their strategies and use of leverage.

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Table 7: Estimation Results 2: Average Leverage

	Logit Model		Random Coef. Model	
Variables	Estimates	Std. Err.	Estimates	Std. Err.
Constant	-14.207	0.251	-13.889	0.467
Rate of Return $t-1$	14.438	1.751	14.156	2.875
Rate of Return $t-2$	13.420	1.845	12.621	3.015
Rate of Return $t-3$	9.531	1.968	10.150	3.087
S.D. Retrun $t-1$	-1.163	1.509	-1.344	2.578
S.D. Retrun $t-2$	-5.288	1.711	-5.642	2.844
S.D. Retrun $t-3$	-9.170	1.780	-8.105	2.760
Year Dummy 2008	-0.296	0.084	-0.254	0.133
Year Dummy 2009	0.093	0.098	0.109	0.155
Year Dummy 2010	0.044	0.098	0.028	0.156
Year Dummy 2011	0.090	0.107	0.073	0.165
Management Fee	-0.058	0.034	-0.069	0.107
Incentive Fee	-0.009	0.006	-0.020	0.012
Maximum Leverage - Mean	–	–	–	–
Maximum Leverage - S.D.	–	–	–	–
Aevrage Leverage - Mean	0.274	0.088	-1.207	0.185
Average Leverage - S.D.	–	–	1.608	0.346
Redemption Freq.	0.297	0.036	0.279	0.070
Lockup Period	-0.023	0.024	-0.023	0.038
Strategy Dummy				
Convertible Bond	0.123	0.216	0.175	0.362
Dedicated Short	-0.758	0.619	-0.821	0.457
Emerging Market	0.047	0.198	0.048	0.284
Equity M. Neutral	-1.046	0.201	-0.801	0.344
Event Driven	-0.062	0.176	-0.045	0.253
Fixed Income	0.512	0.263	0.349	0.455
Fund of Funds	-0.185	0.176	-0.319	0.256
Global Macro	1.280	0.206	1.083	0.345
Long/Short Eq. Hedge	-0.401	0.159	-0.390	0.225
Managed Futures	-0.134	0.182	-0.233	0.295
Multi Strategy	0.292	0.194	0.436	0.285
Option Strategy	-0.119	0.332	-0.076	0.470