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On the failure of mutual fund industry regulation

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ABSTRACT

Mutual funds grant retail investors access to professional asset management and facilitate exposure to financial markets. The academic literature and regulators have traditionally focused on issues such as portfolio diversification, performance, liquidity, and management fees in attempts to analyze and improve market efficiency. Scarce attention has been paid to market risk management. There is unanimity on this issue throughout the world. The lack of regulatory attention creates a gap, which is partially covered by mutual fund rating agents and asset management analysts. Those agents base their ratings on various rating methodologies — which engenders a wide array of difficulties, especially for retail investors. We employ proprietary data on historic mutual fund ratings in Israel and show that retail investors do not necessarily benefit from this diversity of opinions. Furthermore, we find that the *voluntary* implementation of quantitative risk measurement techniques by certain mutual funds tends to be associated with fewer outflows and greater inflows in these funds. Interestingly, the application of (backward-looking) value-at-risk analysis is associated with fewer outflows, while (forward-looking) stress-testing techniques are associated with greater inflows. Given the similarity of mutual fund industry environments across the globe, our results have worldwide applicability.

1. Introduction

Mutual funds, including exchange-traded funds, have become a popular means for income generation, capital appreciation, and diversification for retail investors, providing them with professional money management, asset liquidity, and the benefits derived from diversification at a relatively low cost. In addition to enabling retail investors easy access to professional asset management, mutual funds play an important role in financial markets by improving market liquidity, creating expertise in various asset classes and financial instruments, and enhancing competition in the financial services industry.

Unfortunately, this specific financial instrument may incorporate market risks that do not necessarily conform to the risk profile of every single investor. Furthermore, the measurement and management of market risks in the mutual fund industry have taken a back seat to other issues, such as liquidity risks, enhanced portfolio diversification, and the improvement of operational market efficiency, in both the academic and regulatory literature. The lack of a standard scale to measure and rate market risks across the mutual fund industry has created a gap that has been filled by rating agents and asset management analysts who employ diverse rating methodologies, engendering a wide array of difficulties and discord.

One difficulty comes in the form of potential conflicts of interest. The rating agents operate to attain their own goals, which do not necessarily coincide with investor protection or the improvement of the market's overall economic utility. The diversity of risk

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assessment methods may not pose a problem for certain asset classes, such as equities or bonds, for which myriad opinions are vital to effective market operations. But in the mutual fund market, which is characterized by a high degree of market segmentation, the lack of standards for comparative analysis can cause major distortions, which may impinge on both investor protection and market efficiency.

In most cases, retail investors will not pursue and will not be offered analyses of mutual funds other than that given by the institution (typically a bank) that proposes a specific fund to them. The consequence of this is the de facto suppression of information and access to mutual funds that are either not rated or have been given a low rating by the rating agent used by the institution. This absence of potentially relevant information may contribute to suboptimal investment decision making by retail investors.

Another difficulty is reflected in the potential systemic effects mutual funds may have on financial markets and the economy under various scenarios of financial stress. The failure to properly address market risks can be crucial for retail investors and can also potentially harm the entire industry.

We employ data from the mutual fund industry in Israel during the period 2010–2015, which includes, inter alia, a proprietary indicator of the fund managers' application of quantitative risk measurement techniques. We then match this data with a proprietary historic database of mutual fund ratings rendered by several rating agents. First, we undertake a cross-sectional analysis of fund ratings to demonstrate that the analyses of various rating agents significantly differ. These ratings often include diametrically opposed buy and sell recommendations. The diversity of opinions is acceptable, and even valuable in certain circumstances, but given the segmental structure of the mutual fund market, it could be detrimental to retail investors. Second, using the entire panel, we show that the various rating agents appear to affect investor choices differently, suggesting a clustering of the ratings information. In addition, our findings suggest that the fund managers' application of quantitative market risk measurement techniques is correlated with retail investor decision making. The backward-looking value-at-risk (VaR) market risk measurement technique is associated with fewer outflows, while forward-looking stress-testing techniques (Stress) are correlated with greater inflows. The latter findings suggest that the selection of risk management techniques can be beneficial to a mutual fund in terms of the flow of funds. At the same time, however, a positive VaR or Stress coefficient in the regression models might not necessarily be a truthful measure of causality. Moreover, we show that applying market risk management techniques is associated with better mutual fund performance.

We propose an integrative approach to the analysis of market risk measurement in the mutual fund industry that incorporates *both* mutual fund and rating agent analyses. The results can increase retail investor protection and improve overall utility. Regulators should assess the benefits of adopting quantitative risk models at the relevant rating agents.

Bearing in mind the difficulties outlined above, one should consider the current economic and business environment and the discussion about the proper amount and means of applying regulation in the financial industry. It has been argued that while new regulation was clearly needed in the wake of the financial crisis, some of the new rules have proven overly complex and burdensome.[1] We suggest that these claims should be taken into account when considering new regulatory measures. Unilateral mandatory regulation addressing the entire mutual fund industry could create a nonproductive financial burden if it does not take into account the specific and unique characteristics of each fund.

Our recommendation, at this stage, is that each mutual fund manager should discuss and consider the net benefits (or costs) of implementing quantitative risk measurement in the fund's operating mechanism with the fund's board of directors. The knowledge and understanding of each specific fund gives fund managers the advantage of being able to assess the marginal utility derived from the implementation of risk measurement models.

Recognizing and assessing patterns that are common to the various mutual funds will only be possible after an initial screening performed by the mutual fund managers. Yet such assessment will allow regulators to examine a standard method that can be applied to the entire mutual fund industry. This process would enhance the financial stability of the industry and benefit investors by enabling better compatibility between their personal risk profiles and their asset portfolios.

2. Cross-country regulatory framework

An important lesson emerging from the 2007–2008 financial crisis was that financial institutions must more effectively control financial leverage, asset risk, and maturity transformation to endure periods of extreme stress.[2] The financial crisis precipitated comprehensive reforms of the financial system, including revision of liquidity requirements articulated in the Basel Commission for Bank Supervision's Basel III Accord and the Dodd–Frank Wall Street Reform and Consumer Protection Act. Additional regulatory reforms focus on so-called "shadow banking" activities and proposed changes to the oversight of credit rating agents.

Adrian and Ashcraft (2012) argue that the dilemma facing postcrisis regulatory reform is that the motivation to engage in shadow banking intensifies as the gap between capital and liquidity requirements for traditional banks and nonbank institutions increases. They conclude (p. 137) that

> the objective of reform should be to reduce the risks associated with shadow maturity transformation through more appropriate,

[1] For example, The Glass–Steagall Act of 1933 in response to the Wall Street Crash of 1929 contained 37 pages; the Dodd–Frank Act of 2010 contained roughly 2,300 pages. Basel I had seven risk calculations and seven risk categories; Andy Haldane of the Bank of England has estimated that Basel III has 200,000 categories and could require over 200 million calculations (http://www.telegraph.co.uk/business/2016/08/12/too-much-regulation-will-choke-the-economic-recovery/).

[2] For example, Mohsni and Otchere (in press) show that the U.S. precrisis banking system was associated with relatively high bank risk taking. Thus, this system was not prepared for the crisis.

properly priced and transparent backstop—credible and robust credit and liquidity puts. Regulation has done some good, but more work needs to be done to prevent shadow credit intermediation from continuing to be a source of systemic concern.

Bhojraj et al. (2012) claim that regulatory changes in the mutual fund industry may have reduced selective disclosure of information, lowered the quality of sell-side analyst research at large investment banks, and reduced the ability of fund vendors to benefit from the provision of late trading and market timing opportunities (regulatory scrutiny from trading scandals). Assessing the regulation of the mutual fund industry in the United States, one can see that the main regulatory objective is ensuring full and fair disclosure of the funds' activities to investors and protecting investors from abuse by the mutual fund management (e.g. Baumol et al., 1990). While mutual funds are subject to stricter regulation than that imposed on public companies, their regulation is designed first and foremost to prevent fraud and ensure liquidity. Until recently, systemic risks engendered by the mutual fund industry were assumed to be negligible, and hence mutual funds were not subject to the prudential regulation imposed on banks. The paradigm of "enhanced disclosure" currently governing mutual fund regulation leaves market risk issues improperly defined and unaddressed. With the growing importance of the mutual fund market, accelerated by the meteoric growth of exchange-traded funds, systemic risks are more salient (U.S. Treasury Office of Financial Research, 2013). Mutual fund regulation has also been enhanced in the European Union. The Undertakings for Collective Investment in Transferable Securities (UCITS) Directive[3] lays down detailed requirements on eligible assets, investment policies and risk management, valuation rules, CNAV requirements, NAV buffer, and more transparency. The revisions made to the latest version of the Directive (UCITS V) strengthen the prudential regulation of European mutual funds. The Israeli regulatory authority (the Israel Securities Authority, ISA), much like its worldwide counterparts, focuses on exposure requirements, liquidity and credit risks, and management fees, among other issues. Table 1 summaries the main regulatory objectives in the United States, the European Union, and Israel. The table shows that regulatory frameworks are fairly similar across countries. This means that the lessons studied in one country might be highly relevant to others.

3. Regulatory gap

Risk and return and are the two parameters investors take into account when considering investments in financial assets. To properly measure the risk relative to the expected return, the use of quantitative risk measurement models has grown exponentially over the past decade, especially the use of various VaR methodologies in financial institutions. These methodologies include, inter alia, the historical method for VaR, parameter-based VaR, and Monte Carlo simulations, as well as other models (Domínguez and Alfonso, 2004). Since the implementation of Basel II, where regulators enforced the accumulation of minimal capital buffers to cover potential losses due to VaR shocks, the classic VaR model has become the most common risk measurement model in the financial realm.[4]

This model has some clear benefits. First, it can be used in assessing all the market risks that arise from an institution's financial activities. Second, the model's results are summed up in a single number that can be relatively easily understood by both executives and investors. Third, the rationale behind VaR can be applied to various kinds of risk, such as credit risk and operational risk. Fourth, the model takes into account various correlations between assets and can be calculated using a number of methods.

Unlike banking regulation, which incorporates formulas, equations, and detailed risk/return monitoring, mutual fund regulation is primarily focused on returns and, to a lesser extent, exposure. It is well known that the evaluation of financial performance considers risk and return in tandem. The lack of a regulatory approach that incorporates market risk measurement has created a vacuum. Investors are left without the information required for investment decision making. This vacuum has been filled primarily by third-party rating agents that analyze, rate, and rank mutual funds. These analyses influence the mutual fund screening and selection process undertaken by both institutional and retail investors.

The number of rating agents has grown as a response to the demand for composite risk and return measurement in financial markets. These agents perform their analyses for their own benefit and do not necessarily endeavor to promote overall economic utility.

For example, for the measurement of risk, rating agents usually use 1, 3, 5, or 10 years of data to calculate historical volatility. While assessments based on these measurements alone may suffice for some funds, they could be misleading when analyzing funds that use derivatives to hedge market risk. Research conducted by Cici and Palacios (2015) dispels the notion that mutual funds that incorporate options in their investment strategy have the ability to generate proprietary information that can lead to superior fund performance relative to funds that do not use options. Cici and Palacios also suggest that the use of options does not necessary lead to higher levels of portfolio risk. Some funds that buy puts for portfolio insurance exhibit much lower systematic risk levels than funds that abstain from option trading. These findings do not support the assertion that option-using funds engage in aggressive risk taking either permanently or temporarily and instead suggest that some mutual funds use options primarily for risk management and hedging.

Furthermore, as Barber et al. (2016) demonstrate, sophisticated investors tend to use complicated benchmarks when assessing fund performance over time. These benchmarks do incorporate parameters for *quantitative risk measurement*, and investment decisions are based on the specific risk profile of the investor.

Retail investors, on the other hand, have been left in the dark; they not only base their investment decisions on partial information

[3] Directive 2014/91/EU, 23 July 2014.
[4] http://www.wiley.com/legacy/wileychi/marketmodels/chapter9.pdf

Table 1
Mutual fund regulatory regimes in the United States, European Union, and Israel.

Subject	United States	European Union	Israel
Legislation	Investment Company Act of 1940 Securities and Exchange Commission (SEC), 2014, Part II — Money Market Fund Reform; Amendments to Form PF; Final Rule, 17 CFR Parts 230, 239, et al., Vol. 79, No. 157, 477340	UCITS Directive Directive 2014_91_EU of the European Parliament and of the Council	Joint Investment Trust Law
Exposure (by asset, currency, geography, government/concern, internal/external management)	+	+	+
Interest rate risk (duration)	+	+	+
Credit risk	+	+	+
Management fee	+	+	+
Valuation and pricing methods	+	+	+
Accounting	+	+	+
Compliance	+	+	+
KYC questionnaire	+	+	+
Tax consequences	+	+	+
Liquidity risks	+	+	+
Quantitative market risk measurement	−	−	−

Note. The table summarize existing regulatory attitudes toward different parts of mutual fund regulation. A "+" stands for existing regulation and "−" for a lack of regulatory attention. UCITS = Undertakings for Collective Investment in Transferable Securities; KYC = Know Your Customer.

but also rely on the benchmarks given by the mutual funds' distributers. These benchmarks do not consistently incorporate parameters for quantitative risk measurement, rendering a suboptimal match between the retail investor's risk profile and the risk taken de facto.

To understand the need for regulation, it is first necessary to outline why the market is unable to achieve an efficient outcome on its own. Much like individuals who practice self-control in order to keep fit, mutual fund managers are expected to voluntarily institute controls and manage reputational risk to attract investors. There is a strong correlation between quantitative risk measurement and investment decision making. Measuring risk in an ongoing and transparent manner becomes more crucial as the risk of underlying assets increase. For the sake of illustration, if a certain mutual fund invests 25% of its assets in equity, and during times of increased volatility or during different periods within a business cycle the risk of the underlying assets changes, the proportion invested in equities should change accordingly.

Voluntary controls, however, rarely take the systemic implications of mutual fund activity into consideration. Chernenko and Sunderam (2014) demonstrate that risk taking by money market funds has consequences for debt issuers that potentially affect the broader economy. They show that otherwise creditworthy issuers may encounter difficulties because of the level of risk undertaken by the funds from which they raise debt. Their findings identify a channel through which risk taking at shadow banks spills over to the economy at large because of frictions in short-term credit markets.

This paper contributes to the above-mentioned literature in two realms: First, the paper emphasizes the "regulatory gap" that appears between the need for quantitative risk measurement reported in the academic literature and the lack of regulatory requirements to address this need. Second, the paper provides new empirical evidence that voluntarily applying quantitative risk measurement analysis could be beneficial not only to the mutual funds but also, and more importantly, to retail investors.

4. Model: integrative regulatory framework for a cost–benefit analysis

The integrative regulatory framework for a cost–benefit analysis, which we suggest in this paper, seeks to maximize total economic utility. We examine four groups of participants: retail investors, mutual funds, rating agents, and regulators.

Our approach assumes a link between voluntary controls and regulatory expenditures (B^*) on the one hand and utility on the other. If neither mandatory nor voluntary controls are applied, mutual funds are likely to default and investors will lose their investment. At the other extreme, should mutual funds expend their efforts entirely on controls, abandoning portfolio management to luck and destiny, they will not survive, and investors will once again lose their money. Between these extremes, certain regulation will contribute to the utility of both mutual funds and clients. Excessive regulation, however, will dilute utility (Figs. 1 and 2).

Assume that mutual fund regulation increases investor utility by helping specific mutual funds weather heavy redemptions during times of distress, manage and mitigate potential contagion from such redemptions, or increase the transparency of the risks undertaken by the funds. In such cases, one can expect that an increase in investor utility will follow the increase in regulatory expenditures. As expenditures on voluntary controls and regulation increase, investor utility is also expected to increase.

Drawing both lines of Figs. 1 and 2 on the same axis helps estimate the overall utility function, which is simply the sum of the mutual fund and investor utility functions (the bold line in Fig. 3). Three points can be defined on the new aggregate utility function: The first, A1, is the maximum utility funds can achieve with voluntary controls. Up to point A1, earnings will enable mutual funds to take care of themselves and no external regulation is required. The second point, A2, is the maximum aggregate utility, which takes the investor utility function into account as well. Although the funds' utility function declines when allocations exceed A1, the

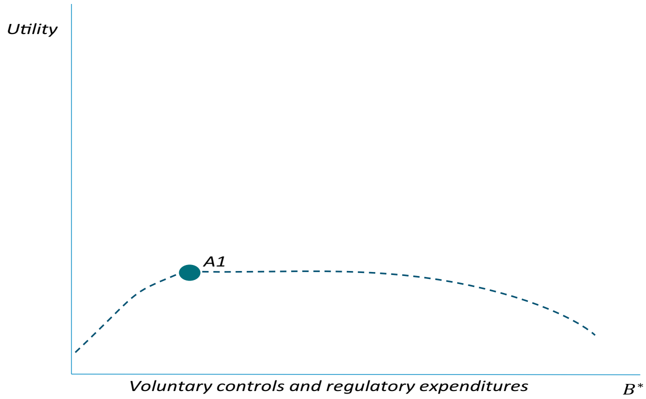

Fig. 1. The relation between voluntary controls/regulation and mutual fund utility. Mutual funds are expected to implement voluntary controls in order to maximize utility (point A1). Up to this point no external regulation is needed because the funds will successfully take care of themselves.

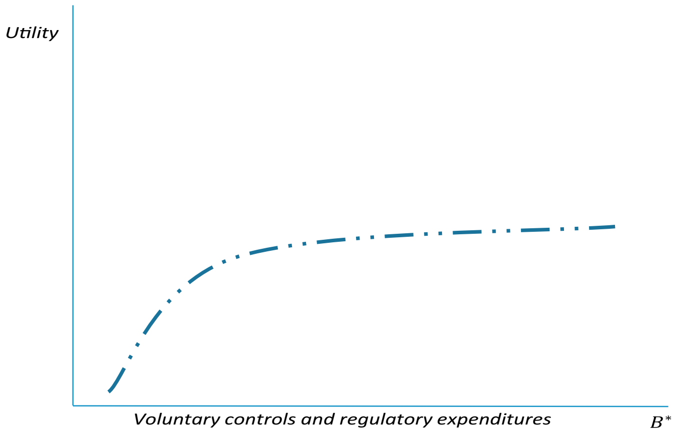

Fig. 2. The relation between voluntary controls/regulation and investor utility.

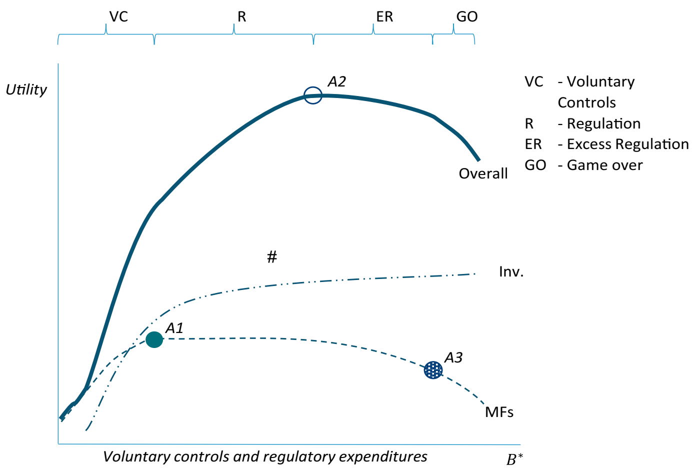

Fig. 3. Aggregation of mutual fund (MF) and investor (Inv) utility.

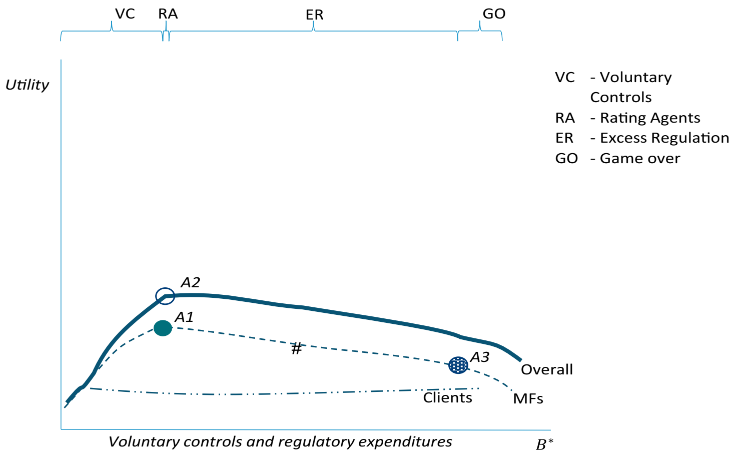

Fig. 4. Rating agents.

investors' utility function continues to increase. If the increase of investor utility exceeds the decline of the funds' utility function, aggregate utility will continue to increase. Otherwise, the maximum aggregate utility will be attained with the same budget for voluntary controls. In this case, no regulation is needed. The third point, A3, signifies that a substantial amount of a fund's utility is allocated to regulatory controls and that if one continues to impose regulation on the fund, it will not survive. This point is a variable and is contingent on the fund's condition.

Using these three points, voluntary control and regulatory expenditures can be divided into four segments:

1. $B^* \leq A1$ indicates a scenario in which funds invest in voluntary controls to maximize their own utility.
2. $A2 \geq B^* > A1$ depicts a scenario in which *additional* regulatory expenditures are required to maximize overall utility.
3. $A3 \geq B^* > A2$, indicates that the intervention of the regulator is too strict and additional regulatory expenditures lead to a reduction of overall utility.
4. $B^* > A3$ represents the termination of fund activity resulting from excessive regulation ("game over").

Rating agents skew the investors' utility function and the aggregate utility function (See Fig. 4). The mutual funds' utility function remains intact, since fund rating does not precipitate greater expenditures. Investors, however, are now exposed to rating agents who endeavor to assist investment advisors and not necessarily investors.

There are two possibilities to restore previous overall utility: regulation of rating agents and/or more effective mutual fund regulation. This theoretical relationship can be estimated statistically and could be examined in future research.

We concur that a blanket decision by the regulator addressing the entire mutual fund industry indiscriminately will create a nonproductive financial burden, as it does not take into account the specific and unique characteristics of each fund. We suggest a framework of targeted regulation that focuses on the implementation of quantitative risk measurement models for specific mutual funds.

5. Benefits of applying quantitative risk measurement models

Our assessment is that the benefits derived from the voluntary implementation of quantitative risk measurement models in the mutual fund industry, considering each fund's specific characteristics and combined with the current regulation, outweigh the costs of implementation. To investigate this hypothesis, we employ a proprietary data set regarding the mutual fund industry in Israel for the period 2010–2015. Our data include an indicator as to whether the fund management company voluntarily applies quantitative risk management techniques — VaR or Stress.

6. Setting

6.1. The Israeli mutual fund industry

Mutual funds in Israel, like their global counterparts, are an important investment vehicle. Local mutual fund investors are almost exclusively retail investors who invest directly in the funds. This investment, in Israel, does not provide investors with any tax benefits, and hence it is not used for retirement savings. As of the end of 2016, the mutual fund industry accounted for 6.3% percent of the public financial assets portfolio. Israel has 1,393 locally managed mutual funds (excluding exchange-traded funds) with

Table 2
Statistics on mutual funds in Israel, by category, as of December 31, 2016.

Category	Total funds	Total fund assets (NIS, millions)	Average portfolio value (NIS, millions)	% of total fund assets
Local bonds, general	334	72,069	215.78	33.7
Local bonds, corporate and convertible	223	32,730	146.77	15.3
Israeli government bonds	198	31,805	160.63	14.9
Money funds	32	18,884	590.13	8.8
Local shares, shekel only	138	20,373	147.63	9.5
Local shares	131	13,217	100.89	6.2
Foreign shares	171	10,464	61.19	4.9
Foreign bonds	98	8,859	90.40	4.1

Note. The table represents the major categories. Amounts in U.S. dollars are about 0.29 of the reported sums in NIS (new Israeli shekels).

approximately 61 billion U.S. dollars under management.[5] While the origins of Israel's mutual fund industry can be traced back to 1940,[6] most funds available today are new, rendering the Israeli mutual fund industry contemporaneously emerging and mature.

Israeli mutual funds operate under the 1994 Joint Investment Trust Law.[7] Table 2 lists the statistics for mutual funds by class, including the number of funds and their asset value in each class, as of the end of 2016.[8]

An in-depth analysis of mutual fund rating agents reveals that Israeli mutual funds are rated primarily by banks, which use in-house analysts to rank funds. These analysts base their ratings on historical data (predominately on a 36-month period), placing an emphasis on the preceding 12 months to evaluate fund returns and volatility. On the basis of these ratings, the banks' investment advisors advise their clients to invest in the top-ranked funds (i.e., the top 20% of the investable market). This marketing process categorically dismisses low-rated mutual funds that make up the bottom 80% of the investable market.

6.2. The Israeli corporate bond market

In contrast to the situation in most countries, including the United States, corporate bonds in Israel are mostly traded on the stock exchange. Like stocks, corporate bonds in Israel are traded on the Tel Aviv Stock Exchange (TASE), which is the only exchange in Israel. Though corporate bonds have been officially traded on the TASE from its inception in 1953, their market value started increasing rapidly only in 2005, following several reforms that liberalized the Israeli capital market. Abudy and Wohl (in press) examine the liquidity of the Israeli corporate bond market and find it to be very liquid in spite of its relatively small size and its relative isolation, with low foreign investor participation. Specifically, they find high volume and low spreads relative to the U.S. corporate bond market. The researchers attribute the high liquidity of the Israeli corporate bond market to the use of a limit order book.

7. Data

Our analysis is based on a proprietary data set that has two major parts. The first part covers 862 mutual fund ratings in common in November 2015 and includes proprietary ratings of three rating agents — two major financial institutions and one rating company that cooperates with a subsidiary of Standard & Poor's (referred to hereafter as agents A, B, and C). These rating agents are three of the five major rating agents in the country, overall. The second part of the data covers 1,470 funds over 68 months, from January 2010 to December 2015. This part consists of the ratings of agents B and C. Moreover, as mentioned above, we have an indication of whether a certain mutual fund applies quantitative risk management techniques — VaR or Stress or both.

The data set enables us to perform three different analyses:

- Cross-section analysis of agents A, B, and C.
- Time series analysis.
- Panel data analysis.

The data set was enriched with the mutual funds' inflows, outflows, size, and rate of return. Tables with the descriptive statistics of the data appear in the relevant parts of the Results section.

[5] ISA, 2016 Annual Report. www.isa.gov.il/sites/ISAEng/1489/1512/Documents/140517.pdf
[6] Stepak (1998) Guide to Mutual Funds in Israel (Hebrew), Meitav, p. 13.
[7] http://www.isa.gov.il/sites/ISAEng/1485/1498/Documents/Joint%20Investment.pdf
[8] ISA, 2016 Annual Report, p. 44.

Table 3
Rating categories.

Category	Agent A	Agent B	Agent C
Strong sell	1	4	1
Sell	2	4	2
Hold	3	6	3
Buy	4	8	4
Strong buy	5	8	5

Note. The table shows rating categories of the three major Israeli rating agents.

Table 4
Mutual fund ratings by agent.

Recommendation	Agent A	Agent B	Agent C
No. of rated funds	1,053	882	1,073
Strong sell	96	131	130
Sell	148		195
Hold	506	498	415
Buy	191	253	200
Strong buy	112		133
%Sell/Strong sell	23.17%	14.85%	30.29%
%Hold	48.05%	56.46%	38.68%
%Buy/Strong buy	28.77%	28.68%	31.03%

Note. The table represent the distribution of the ratings recommendations by agents A, B, and C. Our main specification excludes nonrated funds. For results that include nonrated funds, please see Appendix D.

8. Results

8.1. Cross-section analysis

We start by applying proprietary *cross-section* rating data from three Israeli rating agents, A, B, and C, for November 2015. Two of these agents — A and C — have five rating categories (denoted 1 to 5 in Table 3) while agent B has only three rating categories (denoted 4, 6, and 8 in Table 3).

In November 2015, all three major Israeli rating agents rated 862 mutual funds in common (Table 4).

To compare the ratings of the different agents, we combine the ratings into three categories: (1) sell + strong sell; (2) hold; and (3) buy + strong buy. These categories reflect the differences between the agents' ratings. Although the differences in the buy + strong buy category are relatively small (2.3%), the differences range up to 15.4% in the sell + strong sell category and up to 17.8% in the hold category. Furthermore, drilling deeper into the data, we can see that some mutual funds were rated "sell" by one agent at the same time that they were rated "buy" by another (Figs. 5–7).

Agents A and B rated 495 (57%) of the mutual funds similarly (the green areas in Fig. 5). Eleven mutual funds were ranked by agent A as either "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings by agent B.

Agents B and C ranked 507 (59%) of the mutual funds similarly (the green areas in Fig. 6). Thirteen mutual funds were ranked by agent C as "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings from agent B.

Agents A and C gave the same ratings to 538 (62%) mutual funds (the green areas in Fig. 7). Eighteen mutual funds were rated by agent A as "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings from agent C.

The remaining mutual funds were rated differently (A and B 43%, B and C 41%, A and C 38%), suggesting a mismatch in rating distributions (Fig. 8).

Quantifying this mismatch statistically, we suggest the null hypothesis H0: No difference exists between the agents' rating distributions. The statistical test results are highly significant (Table 5). We reject the null hypothesis and conclude that statistically significant differential rating distributions prevail.

The rating methods differ across the rating agents and there is no guarantee that the rating process incorporates quantitative risk measurement parameters. It is worth noting that retail investors do not necessary benefit from the diversity of opinions outlined above.

For some asset classes, such as equities, competing valuation methods are not barriers, because different opinions and views are integral to the way markets operate. The mutual fund industry, however, is a segmented market. When investors consider investing money in a mutual fund or withdrawing money from it, they are normally presented with only one rating opinion (in most cases the analysis of the institution through which the fund has been acquired) and are not exposed to other analyses and opinions by other rating agents.

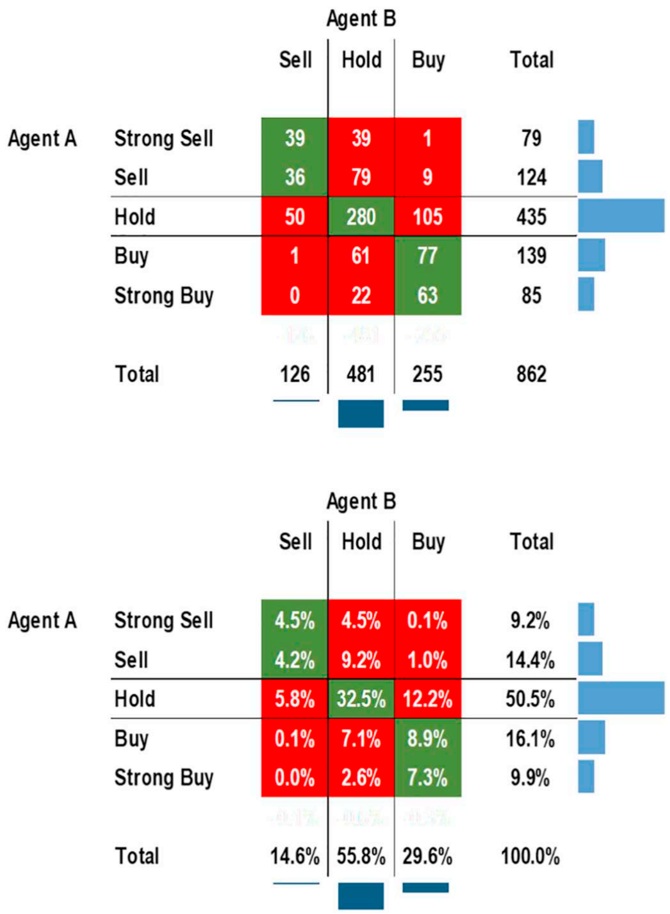

Fig. 5. Rating comparison: Agent A versus agent B.

8.2. Time series analysis

To analyze the stability of ratings over time, we compare mutual fund ratings for each month to the following respective monthly rating of the same fund for 1- to 12-month periods. We choose agent C's ratings, which have five distinctive categories.[9] The spectrum of ratings allows us to better draw the sensitivity of changes. The 1-month and 4-month survival matrices are presented in Table 6 (the illustration of the survival matrix for all months is in Appendix A).

Table 6 shows that after an average period of only 4 months, more than half of the original ratings changed. This finding suggests either the high instability of the rating methodology, or inconsistent performance of the mutual funds, or both.[10]

The picture described — survival behavior of the mutual funds and the confusion of the retail investors — signifies a market failure, warranting regulatory intervention. The regulator should consider regulating mutual fund rating activities, which would compel independent and in-house rating agents to take additional (and essential) variables into account, for example, mutual fund seniority or forward-looking market risk assessments.

8.3. Panel data analysis

For the panel data analyses, we draw on proprietary monthly panel data of agent B's and agent C's ratings for January 2010 to December 2015. The two rating agents, B and C, have 1,470 funds and 68 months in common in the panel data. After data cleansing (Appendix B) the panel has 52,175 fund-month records.

We start with presenting sample statistics for fund sizes, inflows, returns, and outflows. We choose September 2013 as a typical

[9] Applying agent B's ratings gives qualitatively the same picture.

[10] One might add another phenomenon to the findings — in order to insure their survival. Mutual funds often "switch their identity" by establishing a new fund or by significantly changing their investment policy. The "new" fund enjoys 3 years of "flying under the rating radar," which is deemed better than low ratings.

		Agent B			
		Sell	Hold	Buy	Total
Agent C	Strong Sell	57	39	1	97
	Sell	36	115	8	159
	Hold	29	241	73	343
	Buy	1	68	97	166
	Strong Buy	3	18	76	97
	Total	126	481	255	862

		Agent B			
		Sell	Hold	Buy	Total
Agent C	Strong Sell	6.6%	4.5%	0.1%	11.3%
	Sell	4.2%	13.3%	0.9%	18.4%
	Hold	3.4%	28.0%	8.5%	39.8%
	Buy	0.1%	7.9%	11.3%	19.3%
	Strong Buy	0.3%	2.1%	8.8%	11.3%
	Total	14.6%	55.8%	29.6%	100.0%

Fig. 6. Rating comparison: Agent C versus agent B.

		Agent C					
		Str Sell	Sell	Hold	Buy	Str Buy	Total
Agent A	Strong Sell	48	21	10	0	0	79
	Sell	27	56	35	4	2	124
	Hold	20	72	236	89	18	435
	Buy	2	9	47	44	37	139
	Strong Buy	0	1	15	29	40	85
	Total	97	159	343	166	97	862

		Agent C					
		Str Sell	Sell	Hold	Buy	Str Buy	Total
Agent A	Strong Sell	5.6%	2.4%	1.2%	0.0%	0.0%	9.2%
	Sell	3.1%	6.5%	4.1%	0.5%	0.2%	14.4%
	Hold	2.3%	8.4%	27.4%	10.3%	2.1%	50.5%
	Buy	0.2%	1.0%	5.5%	5.1%	4.3%	16.1%
	Strong Buy	0.0%	0.1%	1.7%	3.4%	4.6%	9.9%
	Total	11.3%	18.4%	39.8%	19.3%	11.3%	100.0%

Fig. 7. Rating comparison: Agent A versus agent C.

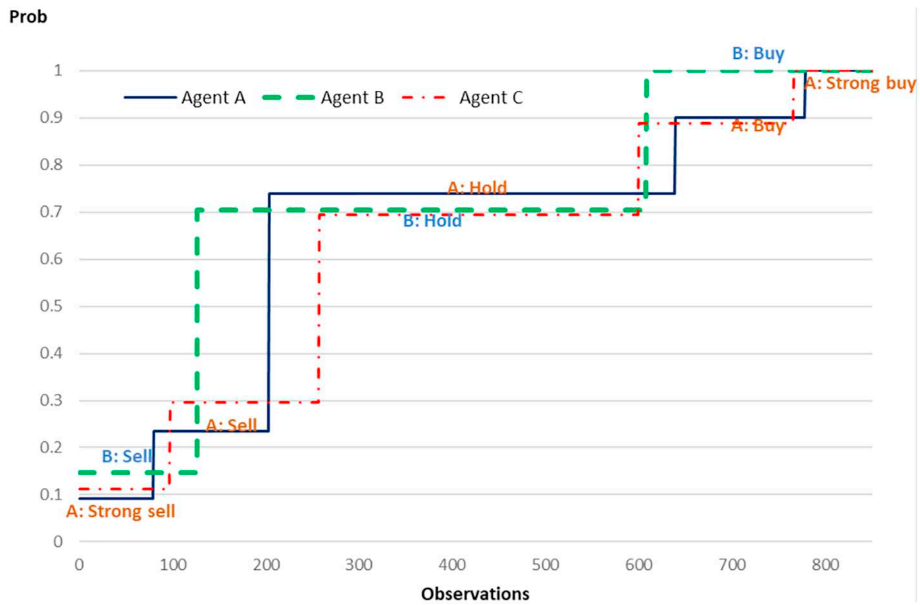

Fig. 8. Empirical CDFs of the agents' mutual fund ratings.

Table 5
Tests for distributions difference between agent ratings of 862 mutual funds.

Test	Agent comparison		
	A vs. B	C vs. B	A vs. C
Pearson χ^2 test			
Pearson χ^2	276.4	423.7	570.1
Degrees of freedom	8	8	16
P value	< .0001	< .0001	< .0001
Likelihood ratio χ^2 test			
Likelihood ratio χ^2	280.6	403.2	496.7
Degrees of freedom	8	8	16
P value	< .0001	< .0001	< .0001
Mantel–Haenszel χ^2 test			
Mantel–Haenszel χ^2	234.8	313.8	376.4
Degrees of freedom	1	1	1
P value	< .0001	< .0001	< .0001
Pearson χ^2 (*df*)	276.4 (8)	423.7 (8)	570.1 (16)
Likelihood ratio χ^2 (*df*)	280.6 (8)	403.2 (8)	496.7 (16)
Mantel–Haenszel χ^2 (*df*)	234.8 (1)	313.8 (1)	376.4 (1)

Notes. The table shows that the differences between the agents' ratings are statistically significant.
All tests $P < .0001$.

month in the middle of the sample period (Table 7). The standard deviations, quartiles, and medians suggest that the distributions of Israeli mutual funds tend to be highly skewed.[11]

In the multivariate regressions that follow, we split our sample into two groups: "large funds" (i.e., greater than the median asset value) and "small funds" (equal to or smaller than the median):

$$scale = \begin{cases} 0\ size \le median \\ 1\ size > median \end{cases}$$

where scale = 1 has 26,067 records, and scale = 0 has 26,108 records.

8.3.1. The model

We start with the following identity equation:

[11] We do not break our sample down by category of mutual fund. This analysis, however, will probably explain some of the variation.

Table 6
Survival matrices of mutual fund ratings by agent C after 1 and 4 months.

Ratings in initial month	Ratings 1		Ratings 2		Ratings 3		Ratings 4		Ratings 5	
	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount
Ratings after 1 month										
Ratings 1	**75.3%**	6,541	12.4%	1,611	1.2%	323	0.2%	25	0.4%	33
Ratings 2	16.7%	1,451	**62.7%**	8,133	11.3%	3,076	0.9%	119	0.3%	23
Ratings 3	3.7%	320	21.5%	2,794	**74.2%**	20,116	23.7%	3,123	4.3%	378
Ratings 4	0.2%	17	0.8%	108	10.7%	2,906	**62.6%**	8,246	18.8%	1,651
Ratings 5	0.3%	25	0.1%	10	1.2%	331	11.9%	1,571	**76.3%**	6,702
Stop ratings	3.8%	328	2.5%	325	1.4%	369	0.6%	81	0.5%	40
Total	100%	8,682	100%	12,981	100%	27,121	100%	13,165	100%	8,787
Ratings after 4 months										
Ratings 1	**51.8%**	4,294	16.2%	2,004	4.3%	1,110	1.8%	221	1.9%	162
Ratings 2	20.8%	1,727	**39.6%**	4,910	16.5%	4,260	5.5%	697	2.1%	179
Ratings 3	11.0%	915	29.1%	3,602	**55.4%**	14,356	34.9%	4,385	14.0%	1,176
Ratings 4	1.5%	126	4.6%	565	14.6%	3,779	**39.9%**	5,019	26.0%	2,192
Ratings 5	1.2%	96	1.1%	133	3.9%	1,014	15.5%	1,945	**54.5%**	4,589
Stop ratings	13.7%	1,139	9.5%	1,181	5.3%	1,375	2.4%	303	1.5%	129
Total	100%	8,297	100%	12,395	100%	25,894	100%	12,570	100%	8,427

Note. The survival matrices show that after an average period of only 4 months, more than half of the original ratings changed. Notations in bold style denote corresponding ratings in an initial month.

Table 7
Mutual fund sample statistics (NIS).

Statistic	Size	Inflows	Outflows	Return
Average	353,230,115	17,977,012	17,471,551	2,788,674
STD	834,444,503	102,544,841	70,620,892	3,761,841
Maximum	11,277,000,000	1,870,818,048	938,201,856	25,581,950
Q3	322,400,000	9,483,373	9,379,367	3,359,880
Median	159,700,000	3,199,721	4,109,356	1,667,540
Q1	70,600,000	1,051,234	1,734,489	705,000
Minimum	4,500,000	–	5,747	(8,757,500)

Note. The table presents the first and second statistical moments and two of the quantiles (Q1, Q3) of the mutual funds' sizes, inflows, outflows, and returns. NIS = New Israel shekels.

Table 8
Sample descriptive statistics of funds rated by agents B and C.

Variable	Small mutual funds		Large mutual funds		*P* value of the means inequality test
	Mean	STD	Mean	STD	
ln_*inflows*($t-1$)	13.1907	1.6512	15.4749	1.5792	0.0001
ln_*outflows*($t-1$)	14.0030	1.1415	16.0268	1.1162	0.0001
ln_*return*($t-1$)	2.2784	12.1888	3.9759	13.405	0.0001
Rating_agent_B	6.0189	1.4188	6.554	1.2763	0.0001
Rating_agent_C[a]	5.7583	1.5432	6.3194	1.5137	0.0001
VaR	0.1444	0.3515	0.198	0.3985	0.0001
Stress	0.1463	0.3534	0.1867	0.3897	0.0001

Note. The right column shows that the differences between small and large mutual funds are statistically significant. VaR = Value-at-risk market risk measurement technique; Stress = stress-testing techniques.

[a] Ratings of agent C were scaled at the same levels as ratings of agent B. This means that for both agents, strong sell and sell ratings are denoted by 4, hold ratings are denoted by 6, and, finally, buy and strong buy ratings are denoted by 8.

$$net\_inflows(t) \equiv size(t) - size(t-1) - return(t)$$ where

$$net\_inflows(t) \equiv inflows(t) - outflows(t)$$

Estimation of the identity equations provides coefficients of zeros and ones. Still, this kind of estimations can assist in data quality verification (see Appendix B).

Table 9
Regression analyses.

Variable	Inflows				Outflows				Return	
	Large size (1)	Large size (2)	Small size (3)	Small size (4)	Large size (5)	Large size (6)	Small size (7)	Small size (8)	Large size (9)	Small size (10)
ln_*inflows* ($t-1$)	0.776206***	0.765833***	0.643335***	0.643306***						
	(0.004070)	(0.003997)	(0.004847)	(0.004747)						
ln_*outflows* ($t-1$)					0.653792***	0.610695***	0.527143***	0.500188***		
					(0.004345)	(0.004441)	(0.004978)	(0.004966)		
ln_*size* ($t-1$)	0.150575***	0.162192***	0.222445***	0.230238***	0.391431***	0.442536***	0.472074***	0.503707***	–0.09707***	–0.09522***
	(0.006649)	(0.006796)	(0.009411)	(0.009559)	(0.005875)	(0.006137)	(0.007205)	(0.007366)	(0.01021)	(0.01906)
ln_*yield* ($t-1$)	0.011131***	0.010741***	0.015945***	0.016672***	–0.00384***	–0.00793***	–0.00320***	–0.00647***		
	(0.000441)	(0.000341)	(0.000673)	(0.000548)	(–0.00384)	(0.000236)	(0.000442)	(0.000367)		
Rating_agent_B	0.040943***	0.039862***	0.063379***	0.057678***	–0.00121	–0.000158	–0.00968***	0.00745**		
	(0.004108)	(0.004282)	(0.005497)	(0.005621)	(0.002659)	(0.002948)	(0.003596)	(0.003758)		
Rating_agent_C	0.078788***	0.082713***	0.098642***	0.101955***	–0.00966***	–0.01270***	–0.00545*	–0.00775**		
	(0.003618)	(0.003768)	(0.005122)	(0.005257)	(0.002255)	(0.002500)	(0.003279)	(0.003438)		
Rating_agent_B									0.00681	0.02596**
($t-1$)									(0.00793)	(0.01227)
Rating_agent_C									0.00878	0.00602
($t-1$)									(0.00668)	(0.01125)
VaR	0.002597	0.002793	0.024341	0.023787	–0.06907***	–0.07959***	–0.03260***	–0.03832***	0.01324	0.04407
	(0.011321)	(0.011858)	(0.018714)	(0.019237)	(0.007411)	(0.008235)	(0.012283)	(0.012894)	(0.02197)	(0.04229)
Stress	0.060915***	0.064835***	0.029259	0.039199**	–0.0031953	–0.0033375	–0.0062228	–0.0063946	0.07605***	0.00839
	(0.011616)	(0.012160)	(0.018543)	(0.019010)	(0.007580)	(0.014220)	(0.012180)	(0.012748)	(0.02258)	(0.04177)
Weighted R^2 (SUR)	0.82	0.79	0.61	0.57	0.82	0.79	0.61	0.57		
Adjusted R^2 (OLS)									0.32	0.32
Observations	51,956	52,020	51,654	51,718	51,956	52,020	51,654	51,718	25,549	25,285
Period fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	Yes
Estimation method	SUR	SUR	SUR	SUR	SUR	SUR	SUR	SUR	OLS	OLS

Note. Large and small size refer to fund sizes (large = greater than the median asset value and small = equal to or smaller than the median); VaR = value-at-risk market risk measurement technique; Stress = stress-testing techniques; SUR = seemingly unrelated regression; OLS = ordinary least squares regression; robust standard errors, clustered at the fund level, are in parentheses. The dependent variables are found in Columns 1–4: monthly inflows (ln), in Columns 5–8: monthly outflows (ln), and in Columns 9–10: monthly returns (%).

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

We then use the system of two equations:

$$\begin{cases} inflows(t) = \beta'\bar{x}^{in} + \varepsilon_{in} \\ outflows(t) = \gamma'\bar{x}^{out} + \varepsilon_{out} \end{cases} \tag{1}$$

where $\bar{x}^{in}$ and $\bar{x}^{out}$ are vectors of the explanatory variables: ln_size(*t*-1), ln_return(*t*-1), rating_agent_B, rating_agent_C, Stress, VaR. The only difference between these vectors is the lag variables, ln_inflows(*t*-1) for $\bar{x}^{in}$ and ln_outflows(*t*-1) for $\bar{x}^{out}$, capturing momentum and serial correlation. A detailed description of the variables is found in Appendix C.

Given the identity equation$size(t) \equiv size(t-1) + inflows(t) - outflows(t) + return(t)$ it is expected that $covar(\varepsilon_{in}, \varepsilon_{out}) \neq 0$.

For the estimation, we selected an econometric method that provides estimation for equations in which residuals are correlated: seemingly unrelated regression (SUR).

We estimate the same SUR model for the two subsamples, as discussed above. One is estimated for the large funds (scale = 1) and the other for the small funds (scale = 0).

8.3.2. Results

Table 8 presents the means and standard deviations of some variables by size of the mutual funds.

As expected, the larger the fund, the higher the statistics.[12] Remarkably, the ratings of large funds appear to be higher, on average, for both agents. The Pearson correlation coefficient between Stress and VaR is approximately 0.5, which might be considered rather high but is still insufficient to raise suspicions of the existence of multicollinearity.

Table 9 summarizes our main results. Columns 1–8 present the estimation results of Model 1. As expected, the contribution of fund size is positive in all regressions; that is, as the size increases, inflows and outflows increase as well, and vice versa. The figures are almost the same for both the large and small funds.

To test the segmentation hypothesis, we assume the opposite—that is, there is no segmentation in the mutual fund market. We split our sample as described above according to mutual funds size into two groups: small (below or equal to the median) and large (above the median). We estimate the same regression for both groups and compare the coefficients for various rating agents. If these coefficients are "close" to each other then we cannot reject the null hypothesis claiming no segmentation. However, if there are differences across coefficients, then we must accept the alternative hypothesis that states that the mutual fund market is segmented.

The ratings of both agent B and agent C contribute positively to the inflows. However, the magnitude of the impact of agent C's ratings is almost twice as high as that of agent B's ratings. While agent C's ratings render the same contribution to inflows in the large-fund subsample as in the small-fund subsample, the contribution of agent B's ratings to small-fund inflows is almost 70% (!) higher than the agent's contribution to large-fund inflows. Furthermore, agent B's ratings have no significant impact on outflows in large funds while agent C's ratings have a significant negative impact on outflows (as agent C's rating increases, outflow decreases). Taken together, these findings suggest the existence of market segmentation.

Although there is no significant contribution of VaR to inflows, there is a significant negative impact of VaR on outflows. Consequently, while there is no significant contribution of Stress to outflows, there is a significant positive contribution to inflows. In this context, the question that needs to be addressed is why Stress contributes to inflows but not to outflows, and why VaR contributes to outflows. Risk managers who use VaR analyses have "historical perspective" — that is, they are *outflow oriented* — while money managers who engage in stress testing are more "forward looking," or *inflow oriented*.

In Columns 9 and 10 in Table 9 we make an attempt to deal with the impact of market risk measurement techniques on the retail investor utility. We estimate gross raw returns[13] of the funds as a function of fund size (*t*-1), fund ratings (*t*-1), VaR, and Stress indicators.

Consider estimating a linear equation of the form

$$y_{it} = \alpha + \beta_1 size_{i,t-1} + \beta_2 B_{i,t-1} + \beta_3 C_{i,t-1} + \beta_4 VaR_i + \beta_5 ST_i + \eta_t + \varepsilon_{it} \tag{2}$$

where y_{it} is the outcome (e.g., monthly return) for mutual fund *i* in month *t*; $size_{i,\,t-1}$ is mutual fund *i*'s size in month $t-1$; $B_{i,\,t-1}$ is an agent B rating in month $t-1$; and $C_{i,\,t-1}$ is an agent C rating in month $t-1$; VaR_i is an indicator for applying VaR analyses in fund *i* and ST_i is an indicator for applying Stress analyses in fund *i*; η_t is a period fixed effect and ε_{it} is an error term clustered at the fund level. In the line with the literature (e.g., see the study by Berk and van Binsbergen, 2015), fund size is negatively correlated with the fund's returns.

Fascinatingly, applying market risk management techniques is positively associated with performance, even though the coefficients are not always precisely estimated. The economic magnitude of applying Stress in the large-fund subsample is relatively high — the nominal gross monthly return climbs by 27.2% (from 0.28% to 0.36%), or by almost 1 percentage point annually. Mutual funds that employ market-risk measurements tend to contribute more to their investors than mutual funds that do not.

It is clear, however, that this association could stem from the omitted variable problem. Companies that manage assets better tend to apply risk management techniques, and VaR or Stress indicators are just proxies for this type of company. However, when we

[12] The exceptions are the standard deviations of the ratings, which are slightly lower than those of the small funds. This finding implies that the ratings of large funds are more homogeneous than those of small funds.

[13] It should be noted that estimating returns net of fees does not qualitatively change our results. We argue that it is more important to measure gross returns than net returns, measuring the division of the "pie" between fund managers and investors. This division could be regulated. Yet, it may be beneficial to extend the analysis to gross risk-adjusted returns, e.g., as measured by α (using several alternative calculation methods).

compare the *same* management companies' pension fund performance, we cannot discern superior performance (Hamdani et al., 2017).

9. Conclusions

The Israeli mutual fund industry, much like its counterparts throughout the world, is a developing financial industry. On the one hand, by facilitating retail investor access to professional investment management, mutual funds increase market liquidity, further expertise in various financial assets and instruments, broaden competition, and enhance nonbank alternatives to the credit market. On the other hand, the absence of a standard rating scale to measure market risks across the industry has created a gap that has been filled by rating agents. This solution has created another difficulty — rating agents who often act in their own self-interest, which does not necessarily align with the protection of investors' interests or the improvement of overall economic utility. Furthermore, the agents base their ratings on various rating methodologies that are not fully disclosed, differ from one agent to the next, and lack the parameters of quantitative risk measurement. This, in turn, precipitates two types of market failure.

The first derives from the mutual fund market being a segmented market. While in other markets, such as equity markets, the plethora of views is an important component of effective trading, in the mutual fund industry, by contrast, retail investors often get their information from a single source. A single rating agent rates a specific fund and places it on a rating scale that is not necessarily understood by others. For all practical purposes, the rating agent "decides" whether a private investor gets information about the fund (if the fund is top rated) or not.

The second type of failure comes from the systemic consequences of the failure to adequately measure market risk. As a financial product, mutual funds have grown in size and volume in the last decade and their systemic importance to financial stability has grown accordingly.

Although mutual funds are already relatively highly regulated, certain issues are not addressed in the current regulation, creating regulatory gaps, particularly in the measurement and management of market risk. Additional regulation should focus on the construction and implementation of a transparent rating scale that will be binding for in-house and independent rating agents and will incorporate quantitative parameters of risk measurement.

However, we recognize the claims made by financial institutions that the regulatory burden requires the deployment of significant resources. As such we recommend that the added regulation be implemented in several stages. The first stage will entail a discussion between the fund managers and their boards of directors about the relevance of implementing quantitative risk measurement for each and every fund under management. Delegation of authority to the managing institution itself will encourage self-regulation, which would be made transparent to investors.

Such an advertisement in the mutual fund industry would benefit fund investors twice over. It would give investors a better understanding of a fund's inherent risks and would enable them to optimally match their specific risk profile to the assets they acquire. Second, quantitative risk measurement assists managers in asset management.

To initiate and impose new rules on the industry, a quantitative cost–benefit analysis is needed. In this paper, we propose an integrative regulatory framework for such an analysis, which is designed to improve overall economic utility. Further research should focus on an empirical estimation of this approach, and on the evaluation of new regulation in terms of overall utility generation.

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Appendix A. Survival matrices of agent C ratings: 1–12 months

Rating in initial month	Ratings 1		Ratings 2		Ratings 3		Ratings 4		Ratings 5	
	%	Amount	%	Amount	%	Amount	%	Amount	%	Amount
Ratings after 1 month										
Ratings 1	75.3%	6,541	12.4%	1,611	1.2%	323	0.2%	25	0.4%	33
Ratings 2	16.7%	1,451	62.7%	8,133	11.3%	3,076	0.9%	119	0.3%	23
Ratings 3	3.7%	320	21.5%	2,794	74.2%	20,116	23.7%	3,123	4.3%	378
Ratings 4	0.2%	17	0.8%	108	10.7%	2,906	62.6%	8,246	18.8%	1,651
Ratings 5	0.3%	25	0.1%	10	1.2%	331	11.9%	1,571	76.3%	6,702
Stop ratings	3.8%	328	2.5%	325	1.4%	369	0.6%	81	0.5%	40
Total	100%	8,682	100%	12,981	100%	27,121	100%	13,165	100%	8,787
Ratings after 2 months										
Ratings 1	65.5%	5,604	14.9%	1,904	2.3%	624	0.6%	75	0.7%	65

Ratings 2	19.9%	1,700	52.6%	6,720	13.8%	3,679	2.2%	290	0.9%	75
Ratings 3	6.2%	532	25.2%	3,227	66.3%	17,705	29.7%	3,854	7.2%	625
Ratings 4	0.6%	51	2.1%	264	12.8%	3,425	52.0%	6,742	23.2%	2,021
Ratings 5	0.5%	41	0.3%	40	2.1%	565	14.2%	1,847	67.1%	5,838
Stop ratings	7.3%	624	4.9%	631	2.7%	708	1.2%	157	0.8%	70
Total	100%	8,552	100%	12,786	100%	26,706	100%	12,965	100%	8,694
Ratings after 3 months										
Ratings 1	57.9%	4,877	16.0%	2,009	3.4%	881	1.1%	135	1.4%	122
Ratings 2	20.9%	1,764	44.9%	5,656	15.5%	4,083	3.8%	486	1.5%	126
Ratings 3	8.8%	745	27.8%	3,500	60.1%	15,794	33.1%	4,223	10.5%	903
Ratings 4	1.0%	83	3.4%	422	13.9%	3,667	45.2%	5,765	25.3%	2,165
Ratings 5	0.7%	61	0.7%	85	3.2%	829	15.1%	1,925	60.1%	5,143
Stop ratings	10.6%	894	7.3%	918	4.0%	1,042	1.8%	233	1.2%	101
Total	100%	8,424	100%	12,590	100%	26,296	100%	12,767	100%	8,560
Ratings after 4 months										
Ratings 1	51.8%	4,294	16.2%	2,004	4.3%	1,110	1.8%	221	1.9%	162
Ratings 2	20.8%	1,727	39.6%	4,910	16.5%	4,260	5.5%	697	2.1%	179
Ratings 3	11.0%	915	29.1%	3,602	55.4%	14,356	34.9%	4,385	14.0%	1,176
Ratings 4	1.5%	126	4.6%	565	14.6%	3,779	39.9%	5,019	26.0%	2,192
Ratings 5	1.2%	96	1.1%	133	3.9%	1,014	15.5%	1,945	54.5%	4,589
Stop ratings	13.7%	1,139	9.5%	1,181	5.3%	1,375	2.4%	303	1.5%	129
Total	100%	8,297	100%	12,395	100%	25,894	100%	12,570	100%	8,427
Ratings after 5 months										
Ratings 1	46.4%	3,793	16.2%	1,978	5.0%	1,280	2.4%	303	2.6%	214
Ratings 2	20.4%	1,665	35.1%	4,289	17.2%	4,393	6.6%	819	3.3%	271
Ratings 3	12.8%	1,043	29.7%	3,619	51.5%	13,125	36.8%	4,556	16.2%	1,346
Ratings 4	2.2%	181	5.6%	687	15.1%	3,852	35.5%	4,389	26.3%	2,185
Ratings 5	1.6%	130	1.6%	190	4.5%	1,154	15.6%	1,927	49.7%	4,125
Stop ratings	16.6%	1,359	11.8%	1,439	6.6%	1,687	3.1%	381	1.9%	155
Total	100%	8,171	100%	12,202	100%	25,491	100%	12,375	100%	8,296
Ratings after 6 months										
Ratings 1	41.4%	3,331	16.0%	1,925	5.7%	1,439	3.1%	380	3.5%	289
Ratings 2	20.1%	1,621	31.6%	3,789	17.4%	4,355	8.2%	1,000	4.1%	338
Ratings 3	14.3%	1,149	29.8%	3,573	48.6%	12,188	37.4%	4,552	18.4%	1,506
Ratings 4	2.7%	220	6.8%	811	15.2%	3,825	32.6%	3,967	25.6%	2,092
Ratings 5	2.2%	175	2.0%	242	5.1%	1,288	15.0%	1,822	46.0%	3,756
Stop ratings	19.3%	1,551	13.9%	1,667	7.9%	1,994	3.8%	457	2.3%	185
Total	100%	8,047	100%	12,007	100%	25,089	100%	12,178	100%	8,166
Ratings after 7 months										
Ratings 1	36.9%	2,924	15.6%	1,838	6.5%	1,601	3.7%	446	4.4%	350
Ratings 2	19.6%	1,552	29.1%	3,438	17.3%	4,264	9.3%	1,111	5.1%	413
Ratings 3	15.5%	1,227	29.4%	3,469	46.1%	11,382	37.9%	4,539	20.3%	1,634
Ratings 4	3.6%	287	7.5%	887	15.3%	3,780	29.9%	3,578	25.4%	2,044
Ratings 5	2.6%	205	2.5%	300	5.6%	1,382	14.8%	1,774	42.0%	3,379
Stop ratings	21.8%	1,729	16.0%	1,885	9.2%	2,278	4.5%	536	2.7%	219
Total	100%	7,924	100%	11,817	100%	24,687	100%	11,984	100%	8,039
Ratings after 8 months										
Ratings 1	33.3%	2,595	15.0%	1,743	7.0%	1,692	4.3%	505	5.2%	413
Ratings 2	18.2%	1,423	26.7%	3,110	17.2%	4,173	10.5%	1,237	6.5%	517
Ratings 3	16.8%	1,314	29.0%	3,369	44.0%	10,675	37.9%	4,465	21.9%	1,735
Ratings 4	4.4%	343	8.5%	993	15.2%	3,690	27.7%	3,270	24.8%	1,961
Ratings 5	3.1%	238	3.0%	344	6.2%	1,510	14.3%	1,688	38.3%	3,032
Stop ratings	24.2%	1,886	17.8%	2,068	10.5%	2,547	5.3%	625	3.2%	252
Total	100%	7,799	100%	11,627	100%	24,287	100%	11,790	100%	7,910
Ratings after 9 months										
Ratings 1	29.4%	2,256	14.4%	1,651	7.4%	1,779	5.0%	582	6.0%	469
Ratings 2	17.7%	1,356	24.4%	2,790	17.2%	4,116	11.5%	1,328	7.2%	561
Ratings 3	17.6%	1,354	28.8%	3,292	41.7%	9,965	38.1%	4,416	24.0%	1,867
Ratings 4	5.1%	393	9.3%	1,060	15.2%	3,638	25.5%	2,958	24.1%	1,873
Ratings 5	3.6%	280	3.6%	412	6.6%	1,567	14.0%	1,620	35.0%	2,721
Stop ratings	26.5%	2,035	19.5%	2,232	11.8%	2,827	6.0%	694	3.7%	288
Total	100%	7,674	100%	11,437	100%	23,892	100%	11,598	100%	7,779
Ratings after 10 months										
Ratings 1	25.8%	1,949	13.9%	1,560	7.8%	1,843	5.8%	661	6.8%	522
Ratings 2	17.0%	1,284	22.3%	2,512	17.0%	3,991	12.5%	1,430	8.3%	634
Ratings 3	18.1%	1,370	28.3%	3,178	40.2%	9,439	37.8%	4,308	25.5%	1,954
Ratings 4	6.0%	450	10.2%	1,145	15.1%	3,547	23.4%	2,672	23.2%	1,777
Ratings 5	4.3%	327	4.1%	466	6.8%	1,604	13.6%	1,556	31.8%	2,436
Stop ratings	28.7%	2,170	21.2%	2,387	13.1%	3,073	6.8%	779	4.3%	327
Total	100%	7,550	100%	11,248	100%	23,497	100%	11,406	100%	7,650

Ratings after 11 months										
Ratings 1	22.4%	1,663	13.1%	1,448	8.2%	1,901	6.7%	750	7.5%	567
Ratings 2	16.4%	1,216	20.7%	2,291	16.7%	3,858	13.3%	1,489	9.3%	701
Ratings 3	18.3%	1,356	28.0%	3,100	38.8%	8,955	37.7%	4,227	26.5%	1,997
Ratings 4	6.9%	510	10.6%	1,176	14.9%	3,433	21.7%	2,432	22.8%	1,712
Ratings 5	5.0%	375	4.8%	530	7.1%	1,630	13.1%	1,470	28.8%	2,170
Stop ratings	31.1%	2,306	22.8%	2,517	14.4%	3,324	7.6%	848	5.0%	375
Total	100%	7,426	100%	11,062	100%	23,101	100%	11,216	100%	7,522
Ratings after 12 months										
Ratings 1	19.8%	1,443	12.2%	1,330	8.5%	1,941	7.4%	811	8.3%	610
Ratings 2	15.8%	1,153	19.2%	2,086	16.2%	3,681	14.3%	1,574	10.5%	777
Ratings 3	18.4%	1,343	27.6%	3,007	37.7%	8,568	37.0%	4,077	27.7%	2,051
Ratings 4	7.3%	533	11.3%	1,228	14.6%	3,326	20.5%	2,265	21.8%	1,608
Ratings 5	5.7%	414	5.4%	584	7.3%	1,654	12.6%	1,384	26.1%	1,930
Stop ratings	33.1%	2,416	24.3%	2,641	15.6%	3,534	8.3%	916	5.6%	417
Total	100%	7,302	100%	10,876	100%	22,704	100%	11,027	100%	7,393

Note. The survival matrices show that after an average period of 4 months only, more than half of the original ratings changed.

Appendix B. Data cleansing—size identity validation

To verify data quality, we performed several data-cleansing procedures:

1. Only funds with inflows (t) < size (t-1)
2. Only funds with outflows (t) < size (t-1)
3. Only funds with Agent_B (t) rating < > “.”
4. Only funds with Agent_C (t) rating < > “.”
5. Only funds with $\left|\frac{Diff\,(t)}{size\,(t)}\right| \leq 0.01$where

$$Diff\,(t) = size\,(t) - size\,(t-1) - inflows\,(t) + outflows\,(t) - yield\,(t)$$

To verify rule 5, the OLS regression was run:

$$size\,(t) = \beta_1 size\,(t-1) + \beta_2 inflows\,(t) + \beta_3 outflows\,(t) + \beta_4 yield\,(t) + \varepsilon$$

	Expected coefficient	Estimated coefficient
Size($t-1$)	1	1.00000*** (0.00000675)
inflows(t)	1	1.00107*** (0.00004486)
outflows(t)	–1	–1.00076*** (0.00006386)
Yield(t)	1	1.00053*** (0.00050004)
Observations		52,175
R^2		1.0000
$Pr > \|F\|$		< 0.0001

Note. The regression above verifies the size identity validation. Before the process there were 71,702 observations. After the process of data cleansing, 52,175 (72.8%) records remain.

Appendix C. Description of variables

Variable	Description
ln_*inflows*($t-1$)	Logarithm of the inflows to a fund in the previous month. Inflows are measured in NIS
ln_*outflows*($t-1$)	Logarithm of the outflows from a fund in the previous month. Outflows are measured in NIS
ln_*size*($t-1$)	Logarithm of the size of a fund in the previous month. Size is measured in NIS
ln_*return*($t-1$)[a]	Logarithm of a fund's return in the previous month. Return is measured in NIS
Rating_agent_B	Rating of agent B: 4 = sell/strong sell; 6 = hold; 8 = buy/strong buy
Rating_agent_C	Rating of agent C: To remain in the same scale as Agent B ratings, we convert [1 = strong sell; 2 = sell] to 4; [3 = hold] is converted to 6; and [4 = buy; 5 = strong buy] is converted to 8
Stress	Dummy variable. Funds that use stress tests receive the value of 1; otherwise the value is 0
VaR	Dummy variable. Funds that use value-at-risk analysis receive the value of 1; otherwise the value is 0

Note. The table describes the variables used in the regressions. NIS = New Israeli shekels. Stress = Stress-testing techniques. VaR = Value-at-risk analysis.

[a] We convert all “money” variables into their logarithms (ln). Since the return has negative observations we converted it as follow: ln[*return* (t)] $:= sign\,(return(t)) \times \ln(|return(t)|)$.

Appendix D. Cross-sectional analyses, including the nonrated funds

Table D1
Mutual funds rated by agents.

Ranking	Agent A	Agent B	Agent C
Total funds	1,393	1,393	1,393
No. rated funds	1,053	882	1,073
Strong sell	96		130
Sell	148	131	195
Hold	506	498	415
Buy	191	253	200
Strong buy	112		133
Nonrated	340	511	320
% of rated funds			
% Sell/strong sell	23.17	14.85	30.29
% Hold	48.05	56.46	38.68
% Buy/strong buy	28.77	28.68	31.03
% of total			
% Sell/strong sell	17.52	9.40	23.33
% Hold	36.32	35.75	29.79
% Buy/strong buy	21.75	18.16	23.91

To compare the ratings of the different agents, we combined the ratings into three categories: (1) sell + strong sell; (2) hold; and (3) buy + strong buy. These categories reflect the differences between the agents' ratings. Although the differences in the buy + strong buy category are relatively small (2.3%), the differences in the sell + strong sell category range up to 15.4% and in the hold category up to 17.8%. Furthermore, drilling deeper into the data, one can see that some mutual funds were rated "sell" by one agent but at the same time were rated "buy" by another (Figs. D1–3).

Agents A and B (Fig. D1) rated 495 (35.5%) of the mutual funds similarly (the green areas). Eleven mutual funds were ranked by agent A as "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings from agent B.

Agents B and C (Fig. D2) ranked 507 (36.4%) of the mutual funds similarly (the green areas). Thirteen mutual funds were ranked by agent C as "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings from agent B.

Agents A and C (Fig. D3) ranked 538 (38.6%) of the mutual funds similarly (the green areas). Eighteen mutual funds were ranked by agent A as "sell" or "strong sell" or "buy" or "strong buy" while receiving opposite ratings from agent B.

		Agent B				
		Non-Rated	Sell	Hold	Buy	Total
Agent A	Non-Rated	320	3	10	7	**340**
	Strong Sell	15	39	39	1	**94**
	Sell	27	36	79	9	**151**
	Hold	92	50	280	105	**527**
	Buy	36	1	61	77	**175**
	Strong Buy	21	0	22	63	**106**
	Total	**511**	**129**	**491**	**262**	**1393**

		Agent B				
		Non-Rated	Sell	Hold	Buy	Total
Agent A	Non-Rated	23.0%	0.2%	0.7%	0.5%	**24.4%**
	Strong Sell	1.1%	2.8%	2.8%	0.1%	**6.7%**
	Sell	1.9%	2.6%	5.7%	0.6%	**10.8%**
	Hold	6.6%	3.6%	20.1%	7.5%	**37.8%**
	Buy	2.6%	0.1%	4.4%	5.5%	**12.6%**
	Strong Buy	1.5%	0.0%	1.6%	4.5%	**7.6%**
	Total	**36.7%**	**9.3%**	**35.2%**	**18.8%**	**100.0%**

Fig. D1. Rating comparison: Agent A versus agent B.

		Agent B				
		Non-Rated	**Sell**	**Hold**	**Buy**	**Total**
Agent C	**Non-Rated**	300	3	10	7	**320**
	Strong Sell	25	**57**	**39**	**1**	**122**
	Sell	42	**36**	**115**	**8**	**201**
	Hold	83	**29**	**241**	**73**	**426**
	Buy	41	**1**	**68**	**97**	**207**
	Strong Buy	20	**3**	**18**	**76**	**117**
	Total	**511**	**129**	**491**	**262**	**1393**

		Agent B				
		Non-Rated	**Sell**	**Hold**	**Buy**	**Total**
Agent C	**Non-Rated**	21.5%	0.2%	0.7%	0.5%	**23.0%**
	Strong Sell	1.8%	**4.1%**	**2.8%**	**0.1%**	**8.8%**
	Sell	3.0%	**2.6%**	**8.3%**	**0.6%**	**14.4%**
	Hold	6.0%	**2.1%**	**17.3%**	**5.2%**	**30.6%**
	Buy	2.9%	**0.1%**	**4.9%**	**7.0%**	**14.9%**
	Strong Buy	1.4%	**0.2%**	**1.3%**	**5.5%**	**8.4%**
	Total	**36.7%**	**9.3%**	**35.2%**	**18.8%**	**100.0%**

Fig. D2. Rating comparison: Agent C versus agent B.

		Agent C						
		Non-Rated	Str Sell	Sell	Hold	Buy	Str Buy	Total
Agent A	Non-Rated	129	25	42	83	41	20	340
	Strong Sell	15	48	21	10	0	0	94
	Sell	27	27	56	35	4	2	151
	Hold	92	20	72	236	89	18	527
	Buy	36	2	9	47	44	37	175
	Strong Buy	21	0	1	15	29	40	106
	Total	320	122	201	426	207	117	1393

		Agent C						
		Non-Rated	Str Sell	Sell	Hold	Buy	Str Buy	Total
Agent A	Non-Rated	9.3%	1.8%	3.0%	6.0%	2.9%	1.4%	24.4%
	Strong Sell	1.1%	3.4%	1.5%	0.7%	0.0%	0.0%	6.7%
	Sell	1.9%	1.9%	4.0%	2.5%	0.3%	0.1%	10.8%
	Hold	6.6%	1.4%	5.2%	16.9%	6.4%	1.3%	37.8%
	Buy	2.6%	0.1%	0.6%	3.4%	3.2%	2.7%	12.6%
	Strong Buy	1.5%	0.0%	0.1%	1.1%	2.1%	2.9%	7.6%
	Total	23.0%	8.8%	14.4%	30.6%	14.9%	8.4%	100.0%

Fig. D3. Rating comparison: Agent A versus agent C.

References

Abudy, M., Wohl, A., in press. Corporate bond trading on a limit order book exchange. Rev. Financ.

Adrian, T., Ashcraft, A., 2012. Shadow banking regulation. Ann. Rev. Financ. Econ. 4, 99–140.

Barber, H., Huang, X., Odean, T., 2016. Which factors matter to investors? Evidence from mutual fund flows. Rev. Financ. Stud. 29, 2600–2642.

Baumol, W.J., Goldfeld, S.M., Gordon, L.A., Köhn, M.F., 1990. The Economics of Mutual Fund Markets: Competition versus Regulation. Kluwer Academic, Norwell, Mass.

Berk, J., van Binsbergen, J., 2015. Measuring skill in the mutual fund industry. J. Financ. Econ. 118, 1–20.

Bhojraj, S., Cho, Y.J., Yehuda, N., 2012. Mutual fund family size and mutual fund performance: the role of regulatory changes. J. Account. Res. 50, 647–684.

Chernenko, S., Sunderam, A., 2014. Frictions in shadow banking: evidence from the lending behavior of money market mutual funds. Rev. Financ. Stud. 27, 1717–1750.

Cici, G., Palacios, L., 2015. On the use of options by mutual funds: do they know what they are doing? J. Bank. Financ. 50, 157–168.

Domínguez, J., Alfonso, M., 2004. Applying stress-testing on value at risk (VaR) methodologies. Invest. Manag. Financ. Innovat. 1, 62–73.

Hamdani, A., Kandel, E., Mugerman, Y., Yafeh, Y., 2017. Incentive fees and competition in pension funds: evidence from a regulatory experiment. J. Law Financ. Account. 2, 1–38.

Mohsni S., Otchere, I., in press. Does regulatory regime matter for bank risk taking? A comparative analysis of US and Canada. J. Int. Financ. Markets Inst. Money.

U.S. Treasury Office of Financial Research, 2013. Asset Management and Financial Stability. https://www.treasury.gov/initiatives/ofr/research/Documents/OFR_AMFS_FINAL.pdf.