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Do Mutual Funds Invest in the Recession-Proof Industries Prior to Crisis?

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ABSTRACT

The purpose of this study is to examine whether mutual funds hedge against the risk of recession by increasing their holdings in the recession-proof industries prior to crisis. The empirical setup is built upon a sample of 491,121 mutual funds’ transactions that occurred in the United States prior to the 2008 financial crisis. In addition, the sample includes employment by industry data, relevant stock- and fund-level characteristics, and the fund performance during the recession. The results of conducted cross-sectional regressions indicate that mutual funds do not hedge against the risk of recession by increasing their holdings in the recession-resistant sectors before the upcoming crisis. Additionally, neither do they decrease their holdings in the recession-sensitive industries. Moreover, this study does not find supportive evidence for hypothesis stating that the funds which display high propensity to buy the recession-proof stock prior to crisis are rewarded with superior performance when the market contracts.

Keywords: Mutual funds, hedging, financial crisis, recession-proof industry

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1. INTRODUCTION

Natural fluctuations of the economy consist of periods of expansion and contraction. Numerous recessions have occurred throughout the past decades, including the Great Depression of 1930s and the most recent economic downturn which caused the 2008 financial crisis. At the moment that this paper is being written, the current economic expansion has entered its tenth year. As the ongoing upward economic march becomes the second longest period without economic recession (Casselman, 2019), the uncertainty about robustness of the upcycle raises familiar end-of-cycle warnings. Excess liquidity, high asset prices and long-lasting economic growth are amid the usual red flags (Ball, 2009; Khan, Kogan, & Serafeim, 2012). In particular, excess liquidity on the market exerts pressure on mutual funds to accelerate the fund's pace of finding new assets to invest in (Khan et al., 2012). Consequently, purchases by funds with large capital inflows raise asset prices which are currently at the highest level since the housing bubble in 2007 ("S&P 500 Index," 2019). The market dynamics outlined above combined with a long period without a recession are likely to influence investor's behavior. Broadly accepted behavioral finance approach indicates that when making investment decisions, investors display risk-averse preferences (Kahneman & Tversky, 1979). Hence, fund managers being aware of the upcoming end of the cycle, might engage into certain trading strategies to hedge against the risk of economic downturn. Furthermore, evidence described in Malmendier and Nagel (2011) proves that agents who experienced lower returns during their lifetime are assigned with lower willingness to take financial risk. Consequently, the risk aversion, among fund managers who experienced the most recent severe crisis in 2008, might be pronounced with even larger magnitude.

There is an extensive body of literature which focuses on mutual funds trading strategies. Amid the literature, the vast majority focuses on emerging markets (Grinblatt, Titman, & Wermers, 1995; and Kaminsky, Lyons, & Schmukler, 2004, among others). However, several studies examined mutual funds' performance on declining markets as well. The existing evidence suggests that mutual funds primarily underperform the passive benchmark during expansions, but achieve superior performance during recessions (Fortin & Michelson, 2002; M. Kacperczyk, van Nieuwerburgh, & Veldkamp, 2009; Kosowski, 2006). In order to unveil determinants of mutual fund's extraordinary returns, prior literature investigated fund managers ability to time the market. Treynor and Mazuy (1966) propose a hypothesis that if managers can outguess the market, the volatility of the fund's portfolio that they manage should be higher in years when the market rises and lower when the market declines. However, their results do not provide evidence to support the hypothesis. Latter studies that examine the same relation by using different models reveal similar non-significant results (Elton, Gruber, & Blake, 2012; Henriksson & Merton, 1981). However, there are studies amid the most recent literature that support market timing hypothesis. The growing number of the literature proves that some skillful managers display ability to time the market and, consequently, decrease their exposure to it when they believe that the market will contract. Furthermore, it has been found that fund manager's market timing ability is magnified during recessions (M. Kacperczyk, Nieuwerburgh, & Veldkamp, 2014). Although the mutual funds' superior performance during recession can be partly ascribed to the managers' market timing ability, another major contribution can be due to fund's hedging strategy. Both concepts are someway related, but hedge against the risk of a downturn is not necessarily inherent in market-timing concept. Ability to outguess the market is mostly associated with the risk-seeking behavior (Bolton, Chen, & Wang, 2011) which indicates that managers are primarily focused on finding booming markets in order to boost their payoffs. On the other hand, hedging is interrelated with risk-aversion (Holthausen, 1979). Hence, manager's effort to outguess declining markets and decrease their exposure to them might be omitted by some market timing models.

Hedging strategies among mutual funds have not received much attention from the researchers over the past years. This puzzle, however, is quite comprehensive and includes strategies like maintaining a basket of shorted stocks in portfolio (Eichengreen et al., 1998) or hedging against foreign currency exchange rate risk (Prindl, 1976). To the best of my knowledge, there is one possible trading strategy to hedge against the risk of financial crisis that have not been researched yet. Namely, fund managers who wish to maintain positive performance during economic downturn could increase holdings in companies which operate in the industries that are resistant to economic recession. Prior research indicates that the sector in which company is active significantly co-determines returns for shareholders during crisis (Jiang, Koller, & Williams, 2009). Additionally, Kacperczyk et al. (2005) find evidence that fund managers concentrate their holdings within one industry if they believe that it will outperform the market. Moreover, Roubinchtein and Wallace (2009) identify industries which could be considered as recession-proof based on the data from the 2008 financial crisis. Hence, mutual fund managers, being aware of upcoming end-of-cycle, might increase their holdings in the recession-resistant sectors. As the above described hypothesis can be considered as novel to the existing research, this study represents a compliment to the growing stream of literature on mutual funds trading behavior. Furthermore, better understanding of strategies followed by institutional investors is a topic of significant interest also to practitioners as the evaluation of fund performance provides a practical assistance for the efficient allocation of financial resources to abundant choice of mutual funds. Attempt to contribute into solving this academic puzzle combined with the topic's current relevance have led to the following research question:

Do mutual funds hedge against the risk of recession by increasing their holdings in the recession-resistant industries?

This study focuses solely on the mutual fund managers who represent professional investors. As prior research indicates, professionals display less significant judgmental biases than amateurs due to trainings and broader experience (Shapira & Venezia, 2001). Furthermore, it is in the interest of fund managers that the fund they manage constantly records abnormal positive performance in order to maintain subsequent cash inflows (Sensoy, 2008). Hence, professional investors have substantial motivation and, relatively to the amateurs, broader cognitive resources to hedge against the risk of financial crisis.

The answer to the above stated research question is constructed upon empirical analyses of mutual funds trading behavior around the 2008 financial crisis. Firstly, recession-resistant and recession-sensitive industries are identified by analyzing the employment decline during the 2001 and 2008 recession. Thereafter, cross-sectional regression model is conducted to test relation between stock's industry classification as recession-proof or recession-sensitive and the fund's buying/selling preferences towards particular stock. Moreover, the empirical setup also includes second regression model to examine whether funds that display high propensity to buy recession-resistant stock prior to crisis are rewarded with superior performance during economic downturn. Both regressions consist of set of relevant control variables which are selected based on the previously conducted studies in the field of mutual fund trading behavior. Lastly, additional analysis is conducted for both models to test robustness of the results on a modified sample. In order to identify recession-proof and recession-sensitive industries the sample includes information on employment figures by industry during the period around recessions in 2001 and 2008. The dataset required for the statistical regressions combines information on and mutual fund holdings, attributes and performance, and stock-level characteristics during the period around the 2008 financial crisis. Geographically, this study is limited exclusively to the United States since the CRSP database provides data on the relevant stock characteristics solely for the US companies.

The remainder of this research is structured as follows. Section 2 gives the overview of relevant literature regarding mutual funds trading behavior and sensitivity among industries to economic recession. Moreover, this section presents the hypotheses which will serve as foundation for the research design. Section 3 presents and elaborates on the methodology as well as the sample used in this study. Section 4 provides the empirical results whilst section 5 gives further interpretation of them and concludes.

2. ACADEMIC LITERATURE REVIEW

In this part I will further elaborate on existing literature concerning mutual fund managers' investment decisions. I will touch upon the influence of risk aversion on investors' trading strategies. Furthermore, this chapter will stress the importance of other factors that significantly shape managers' trading behavior. The academic background detailed in this part will serve as a motivation behind my research question and will be used as a foundation for my research design.

In order to present an overview of prior surrounding literature the chapter is structured as follows. Firstly, I will elaborate on importance of risk aversion in investors' investment decisions. Secondly, I will address trading strategies that are common amid mutual funds, including hedging strategies. Moreover, the influence of the business cycle on financial markets will be presented. Finally, the last part will review the literature on the sensitivity of specific industries to economic downturn.

2.1. Risk aversion

2.1.1. Theorical background

Mutual funds manage approximately twenty percent of financial assets of all households in the US (Cederburg, 2008). Such number stresses how important it is to understand the institutional investors' behavior for practitioners and academic researchers. Though mutual fund managers are professionals who have superior cognitive and technical resources, their investment decisions are still influenced by personal preferences. Eagerness to research fund managers' decision-making behavior have contributed to increased popularity among researchers to scrutinize agents' behavior under risk, including risk aversion as one of the main interest.

Research of risk aversion dates back to 18th century when Bernoulli (1738) formed the beginnings of expected utility (EU) theory. By studying the so-called Petersburg paradox, Bernoulli drew a conclusion that instead of expected monetary value, subjects maximize their expected utility. He proposed a logarithmic utility function *U(x)* which displayed declining marginal utility for every extra unit of wealth. By assuming concave utility function, he was the first researcher to implement risk aversion in his model. His work was followed by von Neumann and Morgenstern (1944) who improved the expected utility model. They introduced a way to measure utility and proved expected utility maximization to be a rational decision criterion based on five basic axioms. Both models from Bernoulli as well as von Neumann-Morgenstern (NM) stress the importance of risk aversion as inherent concept of EU theory. If a lottery offers less utility than its excepted monetary value, such situation indicates risk aversion, i.e. within the range of concavity, the function displays higher utility of the expected value W than of the gamble with the same expected value.

Further researches argued that risk-averse preferences do not apply to subjects who face a possible loss, quite the contrary, agents tend to be risk-seeking (Fishburn & Kochenberger, 1979; Hershey & Schoemaker, 1980; Kahneman & Tversky, 1979). Surprisingly, Laughunn, Payne and Crum (1980) uncovered that when subjects were faced with ruinous losses, 64% of executives in their sample switched to risk averse behavior. Limitations of EU model were addressed by Kahneman and Tversky (1979) who presented prospect theory. The Nobel Prize laureate improved the EU model by, among other ameliorations, keeping risk-averse preferences over gains and including risk-seeking behavior over losses. Prospect theory is considered to be the best available overview of how investors make decisions under risk and stresses importance of risk averse preferences in the decision making process.

2.1.2. Risk aversion and hedging practices

An important attribute of risk aversion for this thesis is its relevance as a concept for the ample literature on hedging practices. Among managerial compensation, structure of the tax code and cost of financial distress, risk-averse behavior is an important determinant of firm's hedging policy (Smith & Stulz, 1985). According to the study of Holthausen (1979), the more risk averse an agent is, the more she is willing to hedge. His research shows that if the expected price of the underlying asset is higher than the forward price, then the level of risk aversion is positively correlated with the share of output spent on the hedge. Furthermore, Holthausen (1979) highlights that risk averters display propensity to achieve lower certain return by trading off higher expected return. Consequently, the firm reduces the expected profit in order to improve its hedge. Moreover, Kahl (1983) looks at individuals' holdings of futures contracts as a proxy for propensity to hedge. Evidence described in his research suggests that the level of risk aversion is positively correlated with the futures position. Therefore, more risk-averse subjects hold bigger share of futures to improve their hedge.

2.1.3. Factors stimulating risk aversion

As risk aversion is a significant determinant of investor's hedging and investing decisions, it is of great importance to understand what stimulates risk averse preferences. The existing literature indicates that the level of risk aversion is influenced by numerous factors. One of them was studied by Brunnermeier and Nagel (2008) who argue that relative risk aversion depends on agents' wealth. In their research, they found that in times of increased liquid wealth caused by higher income or capital gains, households are less risk-averse. Contrarily, when the wealth decreases, the share of risky assets in households' portfolio declines which represents an increased level of risk aversion. Another study implies that time-variance of relative risk aversion is correlated with habit formation (Campbell & Cochrane, 1999). The evidence provided in the paper shows that due to increased level of habit, agent's marginal utility is more sensitive to consumption shocks. Hence, formation of new habits leads to higher risk aversion. Chetty and Szeidl (2005) examine habit-like behavior even with closer scrutiny and investigate the effect of consumption commitment of certain durable goods, such as real estate or cars. Results of their study indicate that subjects who are associated with more commitments hold smaller share of risky assets in their portfolio. They conclude their research by stating that commitments similarly to habits make marginal utility more sensitive to the shocks and, therefore, magnify risk aversion amid agents. Another research conducted by Malmendier and Nagel (2011) emphasizes prior macroeconomic experiences as a relevant factor in shaping individual's willingness to take risk. Based on the sample from 1960 to 2007, they test whether subject's risk aversion is correlated with their exposure to economic events throughout their lifetime. Their results indicate that individuals with lower experienced stock market returns display higher level of risk aversion and, hence, invest less in the stock market. Additionally, there is ample literature on other factors that affect risk aversion, for instance, exposition to cultural and political environment during their childhood (Alesina & Fuchs-Schündeldn, 2007; Guiso, Sapineza, & Zingales, 2004; Osili & Paulson, 2008). However, although risk aversion has been broadly studied by numerous researchers, comprehensiveness of this topic still leaves avenues for future research.

2.2. Mutual funds

Mutual fund managers belong to the group of institutional investors. They are responsible for composition of fund's holdings and investment strategies. Similarly to private investors, their investment decisions are driven by various preferences and objectives. Hence, there has been comprehensive research on mutual funds practices. The bulk of literature addresses the long-lasting debate of relative benefits between mutual funds following index and active investing. As index funds benefit from relatively lower transaction costs (Kostovetsky, 2003), abundant literature indicates that actively managed funds, in general, underperform index investing (Fama & French, 2010; Malkiel, 1995). However, several recent studies argue that this underperformance occurs only in expansions, whereas in recessions active funds display superior returns (Fortin & Michelson, 2002; M. Kacperczyk et al., 2009; Kosowski, 2006). Thus, institutional investors are able to benefit from exploiting variance in performance across the business cycle.

Several researchers attempted to test whether relative good performance of active funds could be driven by their ability to time the market. This stream of literature started with Treynor and Mazuy (1966) who studied composition of holdings among 57 mutual funds. They base their research on the hypothesis that if fund managers are able to outguess the market, they should hedge against the risk of recession by decreasing portfolio volatility and, contrarily, increase the volatility during the economic growth. They do not find evidence to prove forecasting ability among institutional investors as only one amid 57 funds displayed significant market timing ability. Further research conducted by Henriksson (1984) tests the ability by looking at the sample of 116 open-end mutual funds from 1968 to 1980. His study, by using a novel model of evaluating market timing performance developed by Henriksson and Merton (1981), finds the ability roughly in 2,5% of the funds. However, several studies among the most recent research examine newer set of data and find positive results (G. Jiang, Yao, & Yu, 2007; Kaplan & Sensoy, 2008). In addition, Kacperczyk et al. (2014) argue that fund's strategy covaries with the stage of the business cycle. Evidence described in their research indicates that average fund manager displays better market-timing ability during recessions, whereas expansions are associated with improved stock-picking skills. As prices are more volatile in crises, systematic risk increases and any information about shocks causing the volatility becomes more valuable (M. Kacperczyk et al., 2009). Fund's portfolios become more sensitive to relevant information about aggregate return. Thus, manager's cognitive ability to process information about specific stocks and consequent change of holdings between expansions and recessions can be a meaningful determinant of the superior performance during crises.

In addition to the literature on market timing, Elton et al. (2012) study whether managers create value by shifting their exposure to different industries. They examine a sample of funds from 1994-2004. Although they find that managers exhibit significant negative timing ability, they stress that the large volume of the negative timing in their research comes from switching investments to high tech industry. Thus, their results are severely driven by the tech bubble. Though the existing literature on fund managers' timing ability is inconsistent, there is increasing number of papers which find significant evidence. Results differ from the prior literature most often due to implementation of novel methods and study of more recent data. On the other hand, the remaining literature that denies market timing hypothesis, does not imply that funds do not hedge against unfavorable market conditions. Ability to outguess the market is mostly associated with risk-seeking behavior (Bolton et al., 2011) which indicates that managers are primarily focused on finding booming markets to increase their performance. Hedging practices, however, are interrelated with risk-aversion (Holthausen, 1979). Hence, manager's effort to outguess declining markets and decrease their exposure to them might be omitted by some market timing models.

The remaining abundant literature focuses on several strategies commonly executed among mutual funds. Prior studies have found that institutional investors pursue momentum trading (De Long, Shleifer, Summers, & Waldmann, 1990) and invest in herding behavior (Grinblatt et al., 1995; Wermers, 1999). Some managers try to exploit informational advantage and concentrate their holdings in areas where they have superior information (Coval & Moskowitz, 1999, 2001). For instance, funds might invest in stocks of locally headquartered companies. Although preference to invest in local stocks can be driven by home bias (French & Poterba, 1991), Coval and Moskowitz (1999, 2001) find evidence that information asymmetry between local and nonlocal investors gives informational advantage to local investors. When it comes to fund's hedging policy, it is crucial to look at the literature on mutual fund's concentration practices among specific industries. Although such funds forgo well-diversified portfolios, Kacperczyk et al. (2005) form a hypothesis that managers add value by increasing exposure to industries which they believe will outperform the market benchmark. Their evidence reveals that concentrated funds indeed perform better than diversified funds. In particular, managers who pursue higher concentration display higher ability to pick better performing industries and choose stocks with higher returns within the industry. Study of

Dellva, Damskey and Smith (2001) provide additional evidence by finding significant positive selectivity among sector funds. Though both researches do not distinguish their sample between recession and expansion period, their finding on positive selectivity could indicate that during or prior to recession, some funds increase their holdings in industries which are less sensitive to economic downturn and offer relatively better return.

2.3. Business cycle

Business cycles refer to continuous periods of expansion and contraction across most of the industries within an economy. Phase of the business cycle determines with high magnitude performance of firms in financial industry (Albertazzi & Gambacorta, 2009). The most recent recession from 2007-2009 proved that if financial institutions do not allocate their capital efficiently, economic downturn can cost them severe loss or even bankruptcy. At the moment this thesis is being written, the United States economy entered its tenth year of sustained growth. As the current economic expansion is likely to become the longest period without recession in the American history (Casselman, 2019), several usual factors indicate the upcoming end of the cycle.

The existing literature stresses several market dynamics that might raise concerns about persistence of economic expansion. During upswings, rising amount of free capital owned by investors exerts pressure on fund managers to increase their investments on the market (Weber, 1997). Highly competitive market for assets together with flood of capital to invest, drives asset prices to abnormally high levels (Khan et al., 2012). Additionally, profit margins rise, financial institutions lend capital on easy terms, firms invest more and newly created jobs mitigate unemployment rate (Weber, 1997). Furthermore, average hourly earnings experience an increase (Hoynes, 1999) which boosts consumers spending. But ultimately the economic upturn weakens, interest rates go up which affects profitability of some investments. As profit margins begin to fall, firms tend to invest less. Instead of developing new ideas, companies seek to sell their inventory in order to maintain positive performance. Though asset prices are associated with high flexibility and adjust to new market conditions relatively easily, wages, especially amid less skilled workers, shift with smaller magnitude. As salary demand exceeds company’s gains in productivity, firms fire workers to cut operational costs which drives unemployment rate up (Weber, 1997). Although it’s hard to specify direct determinants of the business cycle, the above described market dynamics can rise usual red flags for investors.

Present market conditions highlight current relevance of the research question addressed in the thesis. Most features of an expanding economy described in the previous paragraph are visible amid current market dynamics. According to *Investment Company Fact Book* (2019), the net total value of assets owned by mutual funds has been on a steady rise since the crisis in 2008 and reached the peak of 19 trillion U.S. dollars in 2017. This number exceeds the peak from the previous business cycle by roughly 5 trillion. Increased investments by mutual funds are associated with the rising asset prices. At the moment this research is being written, the current S&P 500 Index almost doubles the value of the same index during the most recent housing bubble ("S&P 500 Index," 2019). Furthermore, *Investment Company Fact Book* (2019) implies that at the end of 2018, the unemployment rate on the U.S. market dropped to 3.9 percent compared to 4.1 percent the year before. In addition, average hourly earnings have been recording a continuous steady increase and rose by 3.3 percent in 2018. According to the existing literature, the current market dynamics are clear evidence of the economic upswing. These factors combined with the abnormally long expansion period signal that the next recession might occur anytime soon. Financial firms adjust their strategies in few different ways, but their primary focus is on avoiding overvalued stocks and hedging against the risk of economic contraction (*Global Private Equity Report*, 2019).

2.4. Recession-proof industries

Weber (1997) defines recession as business cycle contraction across majority of sectors within an economy. However, the existing literature implies that sensitivity to economic recession differentiates across sectors. Some industries during economic downturn exhibit ability to generate steady cash flow and, consequently, maintain their regular operations without engaging in cost-cutting practices. Companies within such sectors, generate steady profit margins and do not need to mitigate their operational costs by laying off employees (Weber, 1997). Hence, industry's ability to achieve recession-resistant performance can be seen through indexes of employment changes during crisis (Roubinchtein & Wallace, 2009). Industries that display relatively low employment changes are more resistant to economic contraction. Another factor that determines level of industry's recession-resistance is mentioned by Braun and Larrain (2005) who find evidence that economic contractions have higher impact on the dependent industries. Sectors which naturally rely more on internal financing are more recession-proof. Additionally, Elton et al. (2012) examine returns on a sample of mutual funds from 1994-2004. In their research, they name industries which delivered the best and the worst return during the tech bubble.

When it comes to the recession-sensitive industries, companies within such industries display high dependence on business cycle. When contraction begins, consumer spending decreases (Bernanke, 1981) and so does companies' productivity. In addition, profit margins begin to fall and companies start to lay off workers in order to cut operational costs and improve their performance. Ultimately, industries that display high level of sensitivity to economic declines are associated with increasing unemployment rates during recession (Weber, 1997). Furthermore, correlation with the business cycle is more pronounced among industries that rely mostly on external financing (Braun & Larrain, 2005).

Existing literature indicates that several industries display abnormal sensitivity to recession. Most of the researchers are consistent and indicate that manufacturing industry is highly affected by business cycle fluctuations (Barker, 2011). It is due to industry's severe reliance on consumer spending. During slump, when consumers tend to spend less, employment in manufacturing, particularly of durable goods, declines sharply (Barker, 2011). Furthermore, based on the classification designed by Roubinchtein and Wallace (2009), other industries that are considered to be recession sensitive are Construction, Mining and Logging. Given the evidence on industries abnormally sensitive to economic downturn, it can be assumed that mutual funds decrease their exposure to these industries as part of the hedging strategy against the risk of economic downturn. Therefore, the first hypothesis is formulated as follows:

Hypothesis 1: *Mutual funds decrease their holdings in the recession-sensitive industries prior to economic contraction.*

In contrast to the recession-sensitive sectors, existing data suggests that several industries are able to achieve steady performance throughout the business cycle. The Private Equity Report by Bain & Company published in 2019, refers to the veterinary sector as an industry which is able to generate steady cash flow across the business cycle. The report stresses that pets are being taken care of by their owners during crisis as well as non-crisis periods. A similar conclusion can be drawn from the healthcare industry. Despite the stage of the business cycle, patients require continuous medication and hospitalization. In addition, the same circumstances apply to the education industry and students who attend universities. This statement is supported by Roubinchtein and Wallace (2009) who identify educational and healthcare sectors as recession-resistant. Their study classifies industries based on index of unemployment decline. A positive index indicates that the industry did not experience a decline and can be considered as recession-proof. Given the evidence that certain industries are associated with steady performance during the crisis and that some mutual funds concentrate their holdings within industries that they believe will outperform the market (Kacperczyk et al., 2005), it can be assumed that mutual funds increase their holdings in the recession-resistant industries to hedge against the risk of a downturn. Hence, the second hypothesis is as follows:

Hypothesis 2: *Mutual funds increase their holdings in the recession-resistant industries prior to economic contraction.*

As companies within the recession-resistant sectors are significantly less affected by the negative effects of the business cycle fluctuations, they record a stable employment throughout the business cycle. If the industry does not record an employment decline during recession, it indicates that firms within that industry record stable profit margins and, hence, do not have to cut operational costs by laying off employees (Bernanke, 1981). Therefore, companies within the recession-proof industries are likely to achieve superior performance relatively to the companies in other industries. Based on the above, it can be assumed that funds which increase their holdings in the recession-proof sectors prior to crisis, record a significantly better performance during the economic downturn. Hence, the third hypothesis is as follows:

Hypothesis 3: *Mutual funds that increase their holdings in the recession-proof sectors prior to recession achieve better performance during the economic downturn.*

3. DATA AND METHODOLOGY

This section presents and elaborates on the applicated methodology to investigate whether the hypotheses are compatible with the tests conducted on the authentic data from the period around the 2008 financial crisis. The research consists of two parts which examine (1) relation between mutual fund's trading activity and industry classification and (2) relation between mutual fund's trading activity and the performance during the recession. Both tests include cross-sectional regression models and are described elaborately in the subsequent sections.

3.1. Trading activity

3.1.1. Employment decline by industries

In order to conduct the tests on mutual fund's trading activity across the recession-resistant industries, it is crucial to start with the identification of sector's sensitivity to economic downturn. According to Weber (1997), economic contractions considerably drive the unemployment rates up. Therefore, it can be assumed that recessions are most pronounced in the industries that experience the biggest decline in the employment. Contrarily to this statement, industries that achieve stable employment during recessions can be considered as immune to economic downturn. In order to examine industry's sensitivity to crisis, the industry-level employment data during recessions is investigated. The sample includes two economic contractions, in particular, the recession period after the dotcom bubble in 2001 and the 2008 financial crisis. Although the official monthly dates of the beginnings and ends of the recessions are published by the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER), solely the yearly values of the employment are taken into account. The reason for this is that the employment decline is the eventual consequence of an economic contraction and is observable only after some time the recession begins (Bernanke, 1981). Furthermore, the U.S. Bureau of Economic Analysis database offers the employment values exclusively in the yearly format. Hence, in order to calculate the employment decline during the recessions, two years are examined for the each business cycle when the crises occurred. Specifically, the year when the aggregated employment reached its peak and the year when the employment recorded its trough based on the data from the U.S Bureau of Economic Analysis. For the cycle including the 2001 crisis, the employment peak and employment trough was recorded in 2000 and 2002 respectively. For the 2008 financial crisis, employment reached its peak in 2007 and was at the lowest level in 2009. In order to compute the employment decline during recession, the following formula from the research of Roubinchtein and Wallace (2009) is applied:

$$employment\_decline_{i,c,t} = \frac{employment_{i,c,t} - employment_{i,c,t-2}}{employment_{i,c,t-2}} \tag{1}$$

where *employment* is industry *i*'s employment when the employment trough was recorded in year *t* during business cycle *c*. In case of both recessions, the employment peak was recorded two years prior to the employment trough, hence, year *t*-2 represents the year when the employment reached its peak.

Table 1: Employment decline by industry

This table illustrates employment decline across the industries in the United States during the financial crises followed by the dotcom and the housing bubble. The data on employment comes from the U.S. Bureau of Economic Analysis database.

	Employment decline %	
Industry	2001 crisis	2008 crisis
Agriculture, forestry, fishing, and hunting	-7.26	-3.81
Mining	-1.96	-2.63

Industry	Employment decline %	
	2001 crisis	2008 crisis
Utilities	-2.03	2.02
Construction	1.34	-22.64
Manufacturing	-11.65	-15.31
Wholesale trade	-2.54	-7.32
Retail trade	1.98	-7.69
Transportation and warehousing	-3.68	-8
Information	-7.51	-7.92
Finance and insurance	3.5	-6.24
Real estate and rental and leasing	4.98	-8.2
Professional, scientific, and technical services	-0.73	-2.6
Management of companies and enterprises	0	-0.72
Administrative and waste management services	-7.83	-14.77
Educational services	8.95	4.66
Health care and social assistance	6.03	4.5
Arts, entertainment and recreation	4.06	-4.31
Accommodation and food services	-0.81	-4.99
Government	3.74	1.72
Total	-1.06	-5.48

The results in Table 1 indicate that only Educational services, Healthcare and social assistance, and Government industries do not record an employment decline throughout both recessions. The CDA/Spectrum database, however, distinguishes only the healthcare industry in their sector classification. Hence, for the purposes of the research, only the stock of companies within the healthcare sector is assumed to be recession-proof. When it comes to identifying the most sensitive industries to the economic downturn, most sectors record a decline during both periods. However, the manufacturing sector stands out by recording an abnormally high double digit decrease throughout both recessions. Hence, solely the manufacturing industry is assumed to be recession-sensitive for the necessity of the research. The above described industry classification based on the sensitivity to economic recession is consistent with findings of Roubinchtein and Wallace (2009) who achieve similar results in terms of employment decline across sectors.

3.1.2. Difference in trading activity by industry over time

In order to examine whether mutual funds increase their holdings in recession-proof industries prior to the end of the business cycle, the study focuses on the fund's trading activity. The fund's trading behavior is reflected in the monthly changes in shares. The retrieved data includes buy and sell transactions of particular stocks owned by mutual funds. For each stock in the sample, the dollar value of the transaction is calculated. The formula for that variable is consistent with Fang et al. (2014) who also study mutual funds holdings:

$$buy_{f,s,t} = price_{s,t} \times change_{f,s,t}, \text{if } change_{f,s,t} > 0 \tag{2a}$$

$$sell_{f,s,t} = -price_{s,t} \times change_{f,s,t}, \text{if } change_{f,s,t} < 0 \tag{2b}$$

where $price_{s,t}$ represents stock *s*' price at the end of month *t*. Accordingly, $change_{f,s,t}$ is a difference between number of shares held by fund f at the end of month *t* and previously reported month. Positive value of $change_{f,s,t}$ indicates that the fund purchased new shares in month *t*. On the contrary, the negative value implies that the fund sold previously owned shares. After obtaining the dollar values of monthly stock transactions, the data is grouped by the funds and stocks. Next, the values are aggregated by the respective quarters in order to make the data consistent across the whole dataset. The *buy* and *sell* outcome variables provide the possibility to examine funds total dollar value of buy and sell transactions in each quarter between 2005-2009.

The objective of the first part of the research is to examine whether mutual funds display propensity to increase their holdings in the recession-resistant industries prior to the economic contraction. According to the analysis of the employment conducted in the previous section, only the healthcare sector is distinguished as the recession-resistant industry. Hence, the first part examines whether stock's affiliation with the healthcare industry affects funds trading decisions. Additionally, the model also examines funds trading preferences towards stocks among the industries that are highly sensitive to recession. The employment analysis classifies exclusively the manufacturing industry as the recession-sensitive sector. Hence, this part will investigate whether stocks that belong to the manufacturing industry affect funds trading behavior. The primary objective of the first part of the research is to examine funds' managers trading decisions prior to upcoming end of the cycle.

First analysis compares the percentage trading activity between industries resistant and sensitive to economic recession. The period examined includes quarterly data from 2005 to 2009. The timespan is based on the business cycle dates given by the Business Cycle Dating Committee of NBER. The above given years are chosen in order to examine fund's trading activity throughout the whole business cycle, not solely the pre-recession period. The percentage trading activity is calculated as the difference between percentage buys and percentage sells in the examined quarter. The percentage of buys/sells indicates aggregated by all funds total dollar value of buys/sells as in Equations 2a and 2b, and then divided by the aggregated total dollar value of the stocks within the same industry at the end of the last quarter.

3.1.3. Cross-section with funds' trading activity

Next test is conducted by using cross-sectional regression models. The objective of the models is to scrutinize funds trading behavior prior to economic contraction. According to the Business Cycle Dating Committee of NBER, the 2008 financial crisis began in the 4th quarter of 2007. Therefore, the sample is reduced solely to the deals that occurred before the recession and includes transactions from period 2005 to 2007, excluding the 4th quarter of 2007. The models incorporate the stock's industry classification and set of variables that control for relevant stock characteristics. Additionally, separate regressions are constructed that investigate the activity in terms of buys and sells individually. The first model produces the total dollar value of quarterly aggregated buy transactions, whereas the outcome of the second one represents the total dollar value of quarterly aggregated sell transactions. The formulas of the regressions are as follows:

$$\begin{aligned}\frac{buy_{f,s,t}}{TNA_{f,t-1}} = \alpha &+ \beta_1 Healthcare_{s,t} + \beta_2 Turnover_{s,t-1} + \beta_3 Size_{s,t-1} \\ &+ SizeSquared_{s,t-1} + \beta_4 Book\_to\_market\_ratio_{s,t-1} \\ &+ \beta_5 Return_{s,t-1} + QuarterFixedEffects_t + FundFixedEffects_f \\ &+ \varepsilon_{f,s,t}\end{aligned} \tag{3a}$$

$$\frac{sell_{f,s,t}}{TNA_{f,t-1}} = \alpha + \beta_1 Healthcare_{s,t} + \beta_2 Turnover_{s,t-1} + \beta_3 Size_{s,t-1} + SizeSquared_{s,t-1} + \beta_4 BooktoMarketRatio_{s,t-1} + \beta_5 Return_{s,t-1} + QuarterFixedEffects_t + FundFixedEffects_f + \varepsilon_{f,s,t} \tag{3b}$$

where the dependent variable *buy* or *sell* represents fund *f* total aggregated buy or sale of stock *s* in quarter *t*. The aggregated value is scaled by *TNA* which implies total net asset value (TNA) under the fund's management at the end of the previous quarter *t*-1. Thus, the dependent variable indicates the relative aggregated value of buy or sale transactions to the fund's size. *Healthcare* is a dummy variable equaling one if the stock is classified as part of the healthcare industry, and 0 otherwise. The control variables include other relevant firm characteristics that might influence fund managers' preference towards particular stocks and are selected based on the prior researches on mutual funds holdings (Falkenstein, 1996; Fang et al., 2014). *Turnover* represents stock *s* turnover and is computed by summing natural log of one with dollar trading volume scaled by the stock's market capitalization at the end of the last quarter. *Size* stands for the market capitalization at the end of the previous quarter, and is measured by the natural log of the stock's market capitalization. *SizeSquared* is the square of size and is incorporated in the model to capture possible nonlinear relationship between buys/sells and firm size. *BooktoMarketRatio* indicates the corresponding stock's book-to-market ratio at the end of the earlier quarter. *Return* is the decile rank of the stock's return among all the stocks in the sample at the end of the last quarter. Decile of the stocks with the lowest return equals to one, and decile of the stocks with the highest return is ten. Lastly, the variables *QuarterFixedEffects* and *FundFixedEffects* introduce the fixed effects to the corresponding quarters and funds respectively. When examining the trading across recession-sensitive industries, the dummy variable *Healthcare* changes to *Manufacturing* and equals one when stock *s* belongs to the manufacturing industry. The remaining variables stay unchanged.

Table 2: Control variables summary statistics

This table illustrates summary statistics of the key stock characteristics used as control variables in the regressions testing the trading activity of mutual funds. The summary is based on the transactions examined during the pre-recession subsample (2005 to the 3rd quarter of 2007). *Turnover* is measured by summing the natural log of one with dollar trading volume divided by the stock's market capitalization at the end of the last quarter. *Size* is the lagged natural log of the stock's market capitalization. *BooktoMarketRatio* is the book-to-market ratio at the end of the last quarter. *Return* is the decile rank of the stock's return amid all stocks in the sample at the end of the last quarter; decile of the stocks with the lowest return equals to one, and ten for the stocks with the highest return.

	Mean	S.D.	Q1	Median	Q3
Turnover	13.02	0.77	12.51	13.02	13.52
Size	8.2	1.89	6.79	8.02	9.48
BooktoMarketRatio	0.38	0.2294	0.2155	0.3338	0.5105
Return decile					
1 (low)	-0.5989	0.078	-0.6292	-0.5741	-0.5447
5	-0.0145	0.0254	-0.0323	-0.0149	0.0085
10 (high)	1.68	7.44	0.928	1.15	1.58

The above table reports summary statistics on the relevant stock's characteristics. In order to reduce impact of spurious outliers on the statistical analysis, several constraints were imposed onto the subsample. Firstly, the extreme values of *Turnover* and *Size* variables are excluded. Secondly, the *BMratio* variable is winsorized at the one percent level. Lastly, the observations of the *Return* variable remain unchanged as all the values are ranked in the corresponding deciles which automatically reduces the impact of outliers within this variable. Consequently, the standard deviation amid the control variables is reduced by a significant amount to the values presented in the Table 2.

3.1. Fund performance

The third hypothesis stated in the research implies that the funds which increase their holdings in the recession-proof stock prior to recession, record superior performance during the downturn. Hence, the second part of the research focuses on the relation between the fund's propensity to increase their holdings within the healthcare industry and the fund's latter performance during the consecutive crisis. It is expected that mutual funds which exhibit higher tendency to increase their holdings in the healthcare sector prior to recession achieve better performance during the economic contraction as their holdings are significantly less affected by the negative effects of the downturn.

To examine the cross-sectional differences in the fund's increase in holdings of the healthcare stocks, the *Propensity* variable is constructed. The measure examines funds' propensity to increase their holdings in the healthcare industry based on the funds trading activity in the pre-recession period 2005 to the 3rd quarter of 2007. In order to construct the measure, buy and sale transactions are investigated when computing the fund's propensity to increase holdings in the healthcare sector. Both types of transactions are taken into account as some funds trade large number of shares on both ends, i.e. though the number of the shares bought might be relatively to other funds very high, the number of the shares sold by the same fund can be even higher and, hence, such fund would eventually decrease their holdings. Therefore, the increase in aggregate total dollar value of the healthcare holdings is computed by firstly calculating, for each fund, the difference between the total value of healthcare stock buys and the total value of sales throughout the pre-crisis period 2005 to the 3rd quarter of 2007. In order to produce the relative buys value to the fund's size, the aggregate dollar value of buys is scaled by the fund's average three-year total net asset value from the pre-crisis subsample. Next, the funds are grouped into the corresponding ranks from zero to seven. The rank equaling zero indicates that before crisis the fund did not trade any healthcare stock at all or it decreased its holdings by selling more than buying. The remaining funds are assigned to the respective quantiles where one indicates the funds that purchased the least healthcare stock relatively to their size, and seven indicates the funds that purchased the most.

Table 3: PROPENSITY summary statistics

This table shows, for each rank of the PROPENSITY_INCREASE_HEALTH variable, the key summary statistics of the funds' trade on the healthcare stock during period 2005 to the 3rd quarter of 2007. For each fund, the trade is calculated by calculating the difference between the total dollar value of buys and the total dollar value of sales and, subsequently, dividing the difference by the fund's average TNA from the 2005-2007 period.

Propensity

Rank	Observations	Mean	S.D.	Median
0 (low)	271	-0.0017	0.008	0.0001
1	106	0.0003	0.0001	0.0003
2	106	0.0008	0.0002	0.0008
3	106	0.0015	0.0002	0.0015
4	105	0.0027	0.0004	0.003
5	106	0.005	0.001	0.005
6	106	0.01	0.002	0.01
7 (high)	105	0.05	0.06	0.03
Total	1,011	0.007	0.026	0.0012

Table 3 provides details on the funds' change in the composition of holdings in the healthcare industry prior to the recession. As the table indicates, only the minority of 1,011 observed funds decreased their holdings in the healthcare industry prior to the crisis. Contradictory, the vast majority increased their holdings by achieving the positive trading ratio. Though the numbers are modest amid the first few ranks, the funds among 6th and 7th rank increased their holdings in the healthcare sector on the average by one and five percentage points respectively.

To test whether fund's propensity to increase holdings in recession-resistant industry prior to recession improves the fund's performance during the downturn, a cross-sectional regression model is designed. The model incorporates half-year return as an outcome variable and set of dependent variables. The dependent variables include the measure of fund's propensity to increase holdings in the healthcare sector, and the variables to control for the relevant fund's characteristics. Therefore, the regression model is represented by the following equation:

$$\begin{aligned} Return_{f,h,t} = {} & \alpha + \beta_1 Propensity_f + \beta_2 Expenses_{f,t-1} + \beta_3 Turnover_{f,t-1} \\ & + \beta_4 Size_{f,t-1} + \beta_5 Age_{f,t-1} + YearFixedEffects + \varepsilon_{f,t} \end{aligned} \quad (4)$$

where the dependent variable indicates fund f return in the 1st or the 2nd half h of year t. *Propensity* represents the fund's propensity to increase holdings in the healthcare sector prior to recession. The remaining set of variables serve as control variables for the relevant fund characteristics that might have significant influence on the fund's performance. The *Expenses* variable represents the fund's expense ratio which is computed as the fund's total operating expenses scaled by the corresponding year's net asset value. *Turnover* indicates the fund's aggregated sales or purchases scaled by average net asset value of the fund from the respective year. *Size* is the total value of net assets under the fund's management and is computed by the natural log of the fund's TNA. *Age* is computed as the natural log of years since the fund was offered to the public for the first time. All the control variables are lagged by one year.

Table 4: Fund summary statistics

This table presents summary statistics of the key fund characteristics based on the fund universe examined during the recession subsample (2008 to the 2nd quarter of 2009). All the data on the fund's features is collected from CRSP Survivor-Bias-Free Mutual Fund Database. *Expenses* shows the fund's total operating expenses scaled by the yearly average net asset value. *Turnover* represents the fund's aggregated sales or purchases divided by the yearly average net asset value of the fund. *Size* stands for the total net asset value under the fund's management and is calculated by the natural log of the fund's TNA. *Age* is computed as the log of years since the fund was offered to the public for the first time. All the control variables are reporter in the yearly format and are lagged by one year.

	Mean	S.D.	Q1	Median	Q3
Expenses	0.012	0.005	0.009	0.012	0.015
Turnover	0.566	4.22	0.29	0.58	0.99

	Mean	S.D.	Q1	Median	Q3
Size	4.79	2.31	3.32	4.81	6.42
Age	2.50	0.69	2.3	2.56	2.83

The control variables that are tabulated above are incorporated in the regression model to ensure that β_1 captures the effect of the fund's propensity to increase holdings in the healthcare industry without influence of the fund's expenses, liquidity, size or age. All the controls are selected according to the prior literature on mutual funds trading activity. For instance, Fang et al. (2014) who also study mutual funds' performance include the same variables in their research to control for the relevant funds characteristics.

3.2. Sample

The sample combines data on the industry-level employment, stock- and fund-level information, mutual fund holdings and performance from the period 2005 to 2009. This period contains economic expansion prior to the credit crisis 2005 to the 4th quarter of 2007, and its aftermath reflected in the 19-month recession from the 4th quarter of 2007 to the 2nd quarter of 2009. The data on the employment at industry-level is retrieved from the U.S. Bureau of Economic Analysis database. In order to identify sector's sensitivity to recession on a bigger sample, apart from the 2008 financial crisis, the dataset also entails information on the employment values around the 2001 recession.

The comprehensive data on mutual funds is obtained from the Thomson Financial CDA/Spectrum holdings database and the CRSP Survivor-Bias-Free Mutual Fund Database. The two databases are merged by the MFLink provided by Wharton Research Data Services (WRDS). Furthermore, the sample is combined with the CRSP and Compustat databases in order to incorporate the stock-level data. The CDA/Spectrum database provides details on mutual funds' investment objective and the monthly holdings of US equities based on the SEC public forms filled by the funds or investment companies. The information on the holdings include net change in shares since the last report date, share's price at the moment of the trade and the stock's industry classification. In order to make the values consistent across the whole dataset, the monthly data is grouped into the respective quarters. The CRSP database provides additional input on the funds characteristics including the fund's age, total net asset value, turnover, expense ratio and return. Though the data is in annual format, it is matched with corresponding quarterly values from the CDA/Spectrum database. Lastly, the quarterly stock-level data is retrieved through Compustat and the CRSP databases. It provides details on the company's market capitalization, market value, stock turnover and return. The sample is widen to 2004 in order to compute the previous stock return for the observations in the first quarter of 2005.

Several restrictions are imposed onto the sample in order to make the examined fund universe more appropriable for the research. First one refers to the fund's investment objective. The prior literature indicates that only the actively managed funds display propensity to switch their holdings between industries (Kacperczyk et al., 2005) and, therefore, only these type of funds can display propensity to increase their holdings in the recession-proof equities prior to recession. Hence, the analysis excludes the funds that are passively managed and follow index investing. In particular, the sample is restricted to the funds that are classified by the CDA/Spectrum database as growth, aggressive growth, or growth and income funds. Secondly, the sample is narrowed down to the mutual funds located in the United States. Otherwise it would be impossible to get the information on the relevant fund's characteristics, as CRSP Mutual Fund Database provides data only for this country. Additionally, the 2008 financial crisis formed beginnings and was the most severe on the American market so a relation, if any, between fund's buys and business cycle or fund's buys and performance during the recession should be most pronounced on that market. Last but not least, the sample consists only of the open-end domestic equity mutual funds. Only the ones that manage more than $5 million of total net asset value throughout the whole period are kept.

After choosing the mutual funds and imposing the restrictions, the obtained data is used to examine funds trading activity by industry over time. For the remaining regression models, the sample is divided into two subsamples based on the stage of the business cycle. The first subsample consists of the data from the period 2005 to the 4th quarter of 2007 and is referred to as the pre-recession subsample. The pre-recession subsample consists of the data on 1,307 funds which were involved in over 491 thousand transactions during the examined timespan. The detailed distribution of the deals is depicted in Table 5. The data in this subsample is reported in the quarterly format and is used to study the funds trading activity across the recession-proof and recession-sensitive industries prior to recession.

The second subsample is referred to as the recession subsample and includes observations from the period 2008 to the 2nd quarter of 2009. Though the Business Cycle Dating Committee of NBER reports that the recession began in the 4th quarter of 2007, the second subsample does not include this quarter. The recession began only in December, thus, this quarter also accounts for the return from the last two months of the upcycle. Hence, the 4th quarter of 2007 does not capture solely the return from the recession period and is excluded from the recession subsample. As the subsample takes into account exclusively the first half of 2009, only the fund's half-year return is reported in this year. To obtain consistent values of return across the subsample, year 2008 is also divided into two halves and, therefore, the return variable is reported in the half-year format. The recession subsample is used to test whether the funds' performance during crisis is affected by the funds propensity to increase holdings in the healthcare stock before recession. The number of the observed funds in the recession subsample is 1,016 which is lower than in the pre-recession subsample as some for some funds data on the fund's characteristic and performance during the recession was not available.

Table 5: Sample distribution of transactions

This table illustrates the sample distribution by year and industry in the pre-recession subsample from 2005 to the 3rd quarter of 2007. In total, the sample consists of 1,307 mutual funds. However, some funds do not trade every year, hence the number of funds examined in each year might be different. Panel B tabulates the industry distribution based on the classification provided by Thomson Financial CDA/Spectrum holdings database. The database classifies industry of a company which stock is traded based on a three digit code (100-136).

Panel A: Distribution by year of transaction

	All transactions		Buys		Sells	
Year	N	%	N	%	N	%
2005	178,455	36.34	104,001	35.70	74,454	37.26
2006	187,275	38.13	112,352	38.57	74,923	37.49
2007	125,391	25.53	74,945	25.73	50,446	25.25
Total	491,121	100	291,298	100	199,823	100

Panel B: Distribution by industry

CDA/Spectrum sector classification	All transactions		Buys		Sells	
	N	%	N	%	N	%
Unknown	10,213	2.08	6,520	2.24	3,693	1.85
Aerospace	7,495	1.53	3,809	1.31	3,686	1.84
Agriculture	698	0.14	476	0.16	222	0.11
Airlines	2,971	0.60	1,779	0.61	1,192	0.60
Automobiles	8,839	1.80	5,387	1.85	3,452	1.73
Banks & Savings Institutions	17,245	3.51	10,817	3.71	6,428	3.22
Beverages	4,831	0.98	2,433	0.84	2,398	1.20
Chemicals	10,090	2.05	5,988	2.06	4,102	2.05

CDA/Spectrum sector classification	All transactions		Buys		Sells	
	N	%	N	%	N	%
Computer Hardware Software & Services	56,052	11.41	33,877	11.63	22,175	11.10
Construction & Engineering	9,912	2.02	5,771	1.98	4,141	2.07
Consumer Services	3,674	0.75	2,317	0.80	1,357	0.68
Electrical & Electronics	17,804	3.63	10,825	3.72	6,979	3.49
Miscellaneous	31,460	6.41	17,361	5.96	14,099	7.06
Energy and Fuels	3,332	0.68	1,841	0.63	1,491	0.75
Financial Services	7,177	1.46	4,407	1.51	2,770	1.39
Food & Restaurants	18,800	3.83	10,571	3.63	8,229	4.12
Healthcare	69,313	14.11	42,104	14.45	27,209	13.62
House Wares & Household Items	7,079	1.44	3,891	1.34	3,188	1.60
Industrial Manufacturing	11,966	2.44	7,200	2.47	4,766	2.39
Insurance	9,482	1.93	5,257	1.80	4,225	2.11
Investment Services	13,018	2.65	7,188	2.47	5,830	2.92
Leisure Travel & Equipment	7,544	1.54	4,895	1.68	2,649	1.33
Machinery & Equipment	24,427	4.97	14,497	4.98	9,930	4.97
Media	2,863	0.58	1,734	0.60	1,129	0.57
Metals & Mining	9,578	1.95	5,666	1.95	3,912	1.96
Packaging	2,072	0.42	1,140	0.39	932	0.47
Paper & Forest Products	4,651	0.95	2,719	0.93	1,932	0.97
Publishing & Printing	5,558	1.13	3,460	1.19	2,098	1.05
Real Estate	497	0.10	338	0.12	159	0.08
Retail & Consumer Goods	17,685	3.60	10,037	3.45	7,648	3.83
Semiconductors	25,375	5.17	15,504	5.32	9,871	4.94
Telecommunications	21,309	4.34	13,066	4.49	8,243	4.13
Textiles & Apparel	13,145	2.68	8,370	2.87	4,775	2.39
Tobacco	2,927	0.60	1,443	0.50	1,484	0.74
Transportation	10,968	2.23	6,402	2.20	4,566	2.29
Utilities	19,642	4.00	11,378	3.91	8,264	4.14
Waste & Environment Management	1,429	0.29	830	0.28	599	0.30
Total	491,121	100	291,298	100	199,823	100

4. RESULTS

This part presents the outcome of the tests depicted in the previous section. It also reveals whether the stated hypotheses are supported by the models conducted on the subsamples. The results of the regressions with the reference to the hypotheses are described elaborately in the subsequent sections.

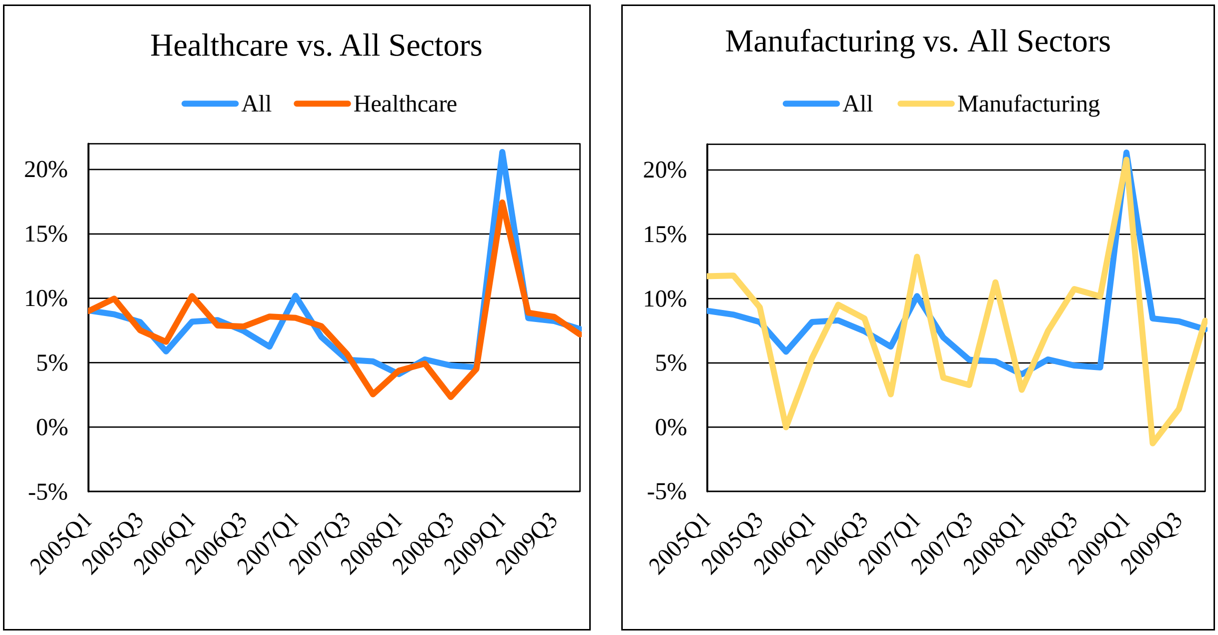
4.1. Difference in trading activity by industry over time

The objective of the first set of tests is to examine whether stocks' industry classification affects the mutual funds' preferences towards that stock. In particular, whether fund managers' increase the fund's holdings in the healthcare sector, and decrease them in the manufacturing sector prior to recession. Before running the regressions, the retrieved data on the funds' transactions creates opportunity to compare percentage trading activity between selected industries. The results of this initial analysis are tabulated below.

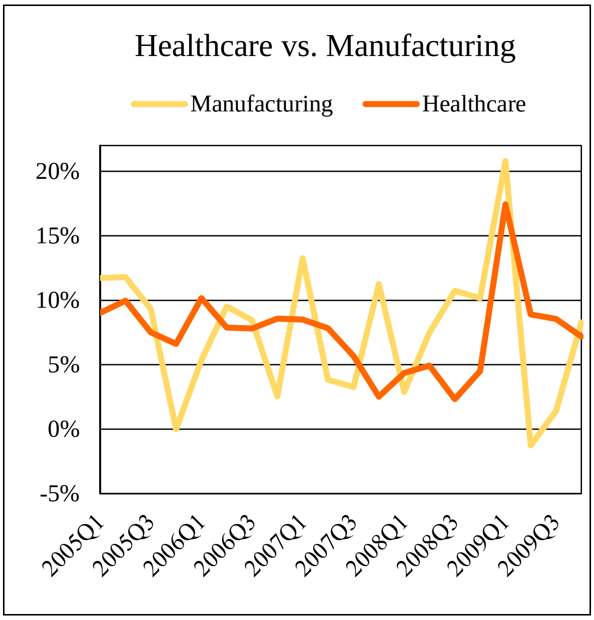
Table 6: Percentage trading activity by industry

This table illustrates the fund's percentage trading activity by selected industries. The period examined includes quarterly data from 2005 to 2009. The percentage trading activity is calculated as the difference between percentage buys and percentage sells in the examined quarter. The percentage of buys/sells indicates aggregated by all funds total dollar value of buys/sells as in Equations 2a and 2b, and divided by the aggregated total dollar value of the stocks within the same industry at the end of the last quarter. The correlations between the variables in each graph are presented in table (d). *, **, and *** imply significance level at the 10%, 5%, and 1%, respectively.

(a) (b)



(c)



(d)

Graph	Correlation
(a)	0.9092***
(b)	0.6000***
(c)	0.3379

The table above examines the relation between aggregate fund percentage trading and stock classification throughout the business cycle. For each quarter, the trading activity is computed by aggregating the total dollar value of buys/sells within the selected industry and dividing this value by the aggregated value of all holdings within the same industry amid all the funds at the end of the previous quarter. To obtain the trading percentage, the percentage of total dollar value of sales is then subtracted from the percentage of buys.

In graph (a), the percentage trading of the healthcare stock is plotted against the trading of all the stock in the examined sample. Both variables record positive values throughout the whole period which implies that the total dollar value of buys of the particular set of stock exceeds the value of sales. Although the graph does not clearly define whether the mutual funds trade the healthcare stock with higher magnitude prior to the beginning of recession in the 4th quarter of 2007, it can be seen that both variables often co-move in the same direction with the similar magnitude. This observation is supported by significantly high correlation which is reported in table (d). The relation is especially pronounced in the 1st quarter of 2009 when both stocks reach their peak.

In graph (b), the percentage trading of all stock in the sample is plotted against the trading of the stock within the manufacturing industry. The manufacturing stock records positive values throughout the whole period, excluding the 4th quarter of 2005 and the 2nd quarter of 2009. It implies that during these quarters, the mutual funds tend to sell the manufacturing stock more than buy. Moreover, the graph illustrates that both variables move mostly in the same direction. However, the manufacturing stock moves with significantly larger magnitude and, hence, displays relatively to the healthcare stock smaller correlation with the trading of all the stocks in the sample.

Graph (c) incorporates the percentage trading within the healthcare and manufacturing industries. The movement of both variables is less consistent than the movement of the variables plotted on the previous graphs. Furthermore, the manufacturing sector displays higher volatility and reaches more extreme values relatively to the healthcare sector. Thus, the correlation between these two variables, in comparison to the relations presented on the other graphs, is lower and statistically insignificant.

4.2. Cross-section with trading activity

This subsection presents the details on fund's trading behavior by incorporating the cross-sectional OLS regression models across buy and sell transactions individually. The dependent variable indicates the aggregated value of buy or sell of the particular stock scaled by the fund's size. The independent variable that represents industry classification is a dummy variable equaling one if stock belongs to the examined industry. The remaining independent variables constitute the set of controls for the stock's relevant characteristics and quarter fixed effects as defined in Equations 3a and 3b. Both regressions investigating the fund's buy and sell behavior are run separately for the healthcare and manufacturing industry.

Table 7: Industry classification and trading activity

This table presents panel regression results of mutual fund's trading activity during the pre-recession period 2005 to the 3rd quarter of 2007. The dependent variables are quarterly aggregated fund buys (panel A) and sells (panel B), divided by the fund's total net asset value at the end of the previous quarter. Healthcare/Manufacturing is a dummy variable equaling one if stock belongs to the healthcare/manufacturing industry and zero otherwise. Stock turnover is computed by summing natural log of one with dollar trading volume scaled by the stock's market capitalization at the end of the last quarter. Size represents the market capitalization at the end of the previous quarter, and is measured by the natural log of the stock's market capitalization. Size squared implies the squared size. B/M ratio indicates book-to-market ratio at the end of the earlier quarter. Past return is the decile rank of the stock's return among all the stocks in the sample at the end of the last quarter. Decile of the stocks with the lowest return equals to one, and decile of the stocks with the highest return is ten. Quarter and fund fixed effects incorporate the fixed effects to the corresponding quarters and funds respectively. OLS robust standard errors are presented in the parentheses below the coefficient parameters. *, **, and *** imply significance level at the 10%, 5%, and 1%, respectively.

	Panel A: Buys/TNA		Panel B: Sells/TNA	
	(1)	(2)	(3)	(4)
Healthcare	-0.0002		-0.0015	
	(0.0010)		(0.0010)	

	Panel A: Buys/TNA		Panel B: Sells/TNA	
	(1)	(2)	(3)	(4)
Manufacturing		-0.0015		-0.0010
		(0.0013)		(0.0011)
Controls				
Stock turnover	0.0017***	0.017***	0.026***	0.0025***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Size	-0.0109***	-0.0109***	-0.0154***	-0.0152***
	(0.0015)	(0.0015)	(0.0022)	(0.0022)
Size squared	0.0009***	0.009***	0.0013***	0.0013***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
B/M ratio	0.0009	0.0010	0.0081***	0.0084***
	(0.0013)	(0.0012)	(0.0021)	(0.0021)
Past return	0.0002**	0.0002**	0.0004**	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Quarter fixed effects	yes	yes	yes	yes
Fund fixed effects	yes	yes	yes	yes
Constant	1.35***	1.35***	0.20***	0.20***
	(0.5283)	(0.5283)	(0.0628)	(0.0628)
Observations	276,589	276,589	193,438	193,438
R^2	0.323	0.3231	0.194	0.194
Adjusted R^2	0.320	0.3199	0.189	0.189

Panel B in Table 7 provides the outcome of the regressions investigating the relation between funds' selling behavior and stock's industry classification. The explanatory variable *Manufacturing* in specification (4) indicates whether manufacturing stock influences fund managers' selling decisions. The variable's coefficient parameter, however, do not provide supporting evidence for hypothesis 1:

Hypothesis 1: *Mutual funds decrease their holdings in the recession-sensitive industries prior to economic contraction.*

Although the coefficient of the *Manufacturing* variable is negative which suggests that funds tend to decrease their holdings in the manufacturing sector, the coefficient is not statistically significant. Hence, the results imply that fund managers do not decrease their holdings in the recession-sensitive industry prior to recession as stock's affiliation with manufacturing industry does not affect the manager's selling preferences. Additionally, specification (3) reports the relation between the healthcare stock and fund's sales prior to recession. Similarly to the previously described specification, the coefficient parameter is negative and statistically insignificant.

Panel A in the same table reports the results of the cross-sectional regression models testing the relation between fund buys of the particular stock and its industry classification. The empirical outcome of specification (1) do not provide evidence to support hypothesis 2:

Hypothesis 2: *Mutual funds increase their holdings in the recession-resistant industries prior to economic contraction.*

In particular, variable *Healthcare* in specification (1) indicates whether the stock within the healthcare sector is more likely to be purchased by the funds' managers prior to recession. The results imply that the affiliation to the healthcare industry decreases the likelihood of the stock being purchased, however, the coefficient parameter is insignificant. Therefore, it can be argued that the fund manager's buying decision is not influenced by the stock's affiliation to the healthcare industry. Thus, the empirics do not provide supporting evidence for the fund's hedging strategy against the risk of recession by increasing their holdings in the healthcare sector, which represents the recession-resistant industry. Furthermore, specification (2) investigates the relation between the manufacturing stock and fund's buys. Although the coefficient is negative which implies that the stock within the manufacturing industry is less likely to be purchased, the result is not statistically significant. Hence, similarly to specification (1), stocks affiliated with the manufacturing industry do not affect fund managers' buying preferences.

4.3. Cross-section with fund performance

This model focuses on the relation between fund's trading activity in the pre-recession period and performance during crisis. In particular, this part investigates whether the funds that display high propensity to increase their holdings in the recession-resistant industries before crisis, achieve superior performance relatively to the other funds, during the recession. The test is conducted by incorporating cross-sectional OLS regression model. The dependent variable represents the fund's half-year return. The independent variables include the measure of fund's propensity to increase holdings in the healthcare stock prior to recession as described in Table 3, and set of other variables which represent controls for the relevant fund characteristics.

Table 8: Trading activity and fund performance

This table reports panel regression results on fund's propensity to buy healthcare stock and future performance based on the sample from 2008 to the 2nd quarter of 2009.The dependent variable is fund's half-year return. Propensity is the decile rank of fund's propensity to increase holdings in healthcare industry during the pre-recession period. For each fund, the increase/decrease in holdings is calculated by calculating the difference between the total dollar value of buys and sales and, then dividing the difference by the fund's average TNA from the 2005-2007 period. The rank of funds that decreased their holdings or did not trade the healthcare stock at all is 0; the remaining funds are assigned to the respective quantiles where 1 indicates the funds that increased their holdings the least, and 7 represents the funds that increased their holdings the most. Expense is the fund's expense ratio. Turnover is the fund's annual turnover. Fund size is the natural log of one and fund's TNA. Age is the natural log of years since when the fund was first offered. All the control variables are lagged by one year. OLS robust standard errors are presented in the parentheses below the coefficient parameters. *, **, and *** imply significance level at the 10%, 5%, and 1%, respectively.

	Coef.	*t*-stat
Propensity	-0.0209	-1.04
	(0.0201)	
Controls		
Expense	-0.5967	-0.40
	(1.5029)	
Turnover	-0.0004	-0.62
	(0.0007)	
Fund size	-0.0094	-2.83***
	(0.0033)	
Age	0.0004	0.04
	(0.0095)	
Year fixed effects	yes	yes
Fund fixed effects	yes	yes
Constant	-0.1036	-1.90*
	(0.0545)	
Observations	2,559	
R^2	0.599	
Adjusted R^2	0.339	

The table above presents the results of the cross-sectional regression model investigating the relation between fund's propensity to increase holdings in the healthcare sector and the fund's latter performance during recession. The empirical outcome tabulated above, however, is not consistent with hypothesis 3:

Hypothesis 3: *Mutual funds that increase their holdings in recession-proof sectors prior to recession achieve better performance during the economic downturn.*

Specifically, the explanatory variable *Propensity* which accounts for the fund's propensity to increase holdings in the recession-proof stock represented by the healthcare industry is insignificant. Such outcome indicates no relation between fund's tendency to buy healthcare stock prior to recession and future performance during the contraction. Furthermore, despite controlling for various fund characteristics, the variable's coefficient parameter is negative which suggests that return rises in inverse proportion to increase of holdings in the healthcare industry. Hence, if the coefficient was significant, it would imply, contradictory to the stated hypothesis, that funds which decreased or did not increase their holdings in the recession-resistant industries are rewarded with higher return during crisis.

4.3. Robustness

Clearly and Angel (1984) stress that in order to compute the most reliable and unbiased linear estimator, homoskedasticity is an essential assumption of the OLS regression coefficient. This assumption indicates that the error term remains the same throughout all values of the independent variables which are independently randomized across the sample. To test for homoskedasticity, the Breusch-Pagan test developed by Breusch and Pagan (1979) is used separately for all regression models presented in this study. The results indicate that homoskedasticity is violated in all the models and, hence, heteroskedasticity exhibits presence in the data. Regarding the coefficient values, White (1980) highlights that heteroskedasticity does not affect economical significance of the coefficient parameters. However, such violation makes the standard errors less reliable which might eventually result in mistaken conclusions regarding statistical significance of the coefficient parameters. Therefore, to address heteroskedasticity and obtain more reliable empirical results regarding the statistical significance, Huber-White robust standard errors are incorporated into all the regression models.

4.4. Additional analysis

In order to establish the robustness of the coefficient parameters that have been presented above, the cross-sectional linear regressions will be performed with few modifications. First of all, the linear regression model investigating the funds' trading activity prior to recession will use an abbreviated pre-recession sample which includes transactions that occurred closer to the economic downturn. Second, the regression examining the relation between fund's buys and their latter performance, uses modified propensity variable which in the additional analysis ranks the funds according to their propensity to buy the healthcare stock during the abbreviated pre-recession period from the first to the third quarter of 2007.

4.4.1. Trading activity

The results of the model testing the fund's trading activity described in table 7 are based on the pre-recession subsample from 2005 to the 3rd quarter of 2007. However, it can be assumed that some determinants of the upcoming recession including abnormally high asset prices (Khan et al., 2012) and low unemployment rates (Weber, 1997) do not achieve abnormal levels by few years before the crisis and, thus, are not obvious indication of approaching end of the cycle. Both measures tend to rise during the upcycle and record the most extreme values right before the recession. It is plausible that shortly before the recession the usual end-of-the-cycle warning signs are pronounced with the largest magnitude and, therefore, increasing number of managers is aware of the potential upcoming contraction and adjust their trading decisions accordingly. The examination of the sample on the period starting from 2005, which is roughly three years before the financial crisis, might not capture solely the trading decisions that are made amid noticeable red flags of the upcoming end of the cycle. Therefore, the objective of the additional analysis is to scrutinize mutual funds' trading behavior by looking at the sample of transactions which occurred closer to the recession.

In order to adjust the examined sample to the additional analysis, the pre-recession subsample is abbreviated to the period from the beginning of 2007 to the 3rd quarter of the same year. Limiting the timespan of the examined transactions to three quarters right before the recession should represent higher influence of upcoming end of the cycle on managers trading decisions as recession determinants like asset prices and employment rates approach their peak levels. The adjusted sample is tested on the same models as presented in Table 7.

The results are presented in table 9 in the appendix and do not provide evidence to support hypothesis 1. In particular, specification (4) implies that manufacturing stocks have higher likelihood of being sold which is in line with the hypothesis, but the coefficient is statistically insignificant. On the buy side, specification (2) reports the statistically significant negative coefficient parameter which suggests that the funds are less willing to buy stocks within the manufacturing sector relatively to the other stocks prior to recession. However, specification (2) serves just as an additional analysis and cannot be perceived as relevant evidence to support any of the hypotheses. Furthermore, the empirics tabulated in the table do not conclude with supporting results for hypothesis 2 which assumes that within the hedging strategy, mutual funds increase holdings in the recession-resistant sectors. Specifically, specification (1) reports significant relation at the ten percent level between the healthcare industry and funds' buys. However, the coefficient is negative which implies that the funds do not increase, but decrease their holdings in the recession-proof industries. Moreover, according to specification (3) in panel B, statistically significant positive coefficient parameter suggests that stock's affiliation with the healthcare industry significantly increases the likelihood of the stock being sold.

4.4.2. Fund performance

Based on the assumptions described in the previous subsection, it can be speculated that abbreviating the pre-recession period might also affect the relation between fund's propensity to increase holdings in the healthcare stock prior to recession and the latter performance. Right before recession when the usual end-of-cycle red flags are more obvious, fund managers might be more aware of upcoming crisis and, consequently, buy the recession-proof stock in order to hedge against the risk of economic downturn. Hence, looking at the abbreviated period creates opportunity to examine funds that might buy the healthcare stock solely for the hedging purposes. Additionally, some funds might attempt to time the market by investing in the recession-resistant stock and, therefore, decreasing their exposure to the market right before the market contracts (Treynor & Mazuy, 1966). Given these assumptions, it is worth investigating whether there is existing relation between funds' buys right before recession and the latter performance. Therefore, the additional analysis defines propensity to buy the healthcare stock by scrutinizing funds' trading activity during the abbreviated pre-recession period which includes first three quarters of 2007. The remaining attributes of the model stay the same.

The empirics are tabulated in table 10 in the appendix and do not reveal supporting evidence for hypothesis 3 which indicates that funds displaying high propensity to increase holdings in the healthcare stock achieve superior performance during crisis. In particular, the propensity variable has negative coefficient parameter which suggests that funds exhibiting tendency to increase their holdings in the recession-resistant stock during the abbreviated pre-recession period, are affiliated with lower future performance during crisis. Such funding is contradictory to the hypothesis, however, the parameter is statistically insignificant.

5. DISCUSSION

In the previous section, results of the conducted tests were presented, which provided answers on the three hypothesis examined in this study. Furthermore, additional analyses contributed to this paper by providing supplementary results related to the scrutinized relations. This final section will firstly summarize this study briefly. Moreover, it will elaborate on results in regards to the existing literature. Lastly, the section will conclude with the limitations and suggestions for future research.

5.1. Summary

The objective of this study was to examine mutual funds' hedging practices against the risk of economic recession. In particular, the research focused on the funds' trading behavior prior to economic contraction. Although the bulk of literature suggests that mutual funds fail to forecast the market and decrease their portfolio's exposure to it accordingly (Henriksson, 1984; Treynor & Mazuy, 1966, among others), several studies provide evidence that some funds tend to concentrate their holdings within sectors that they believe will outperform the market (M. Kacperczyk et al., 2014; M. Kacperczyk et al., 2005). Moreover, the existing literature indicates that there are industries that display different levels of sensitivity to economic recessions (Barker, 2011; Roubinchtein & Wallace, 2009). Both of these findings give rise to the suspicion that mutual funds might increase their holdings in the recession-resistant industries prior to crisis in order to hedge against the risk of an economic downturn and, therefore, achieve superior performance when the market contracts.

This was examined by introducing two cross-sectional regression models. First model consists of two parts. First part investigated whether stock's industry classification as recession-proof or recession-sensitive influences the fund's buying preferences towards this particular stock. The second part studied the same relation but investigated the fund's selling preferences. This model controls for the relevant stock's characteristics that might also influence fund manager's trading decisions. Furthermore, fund and quarterly fixed effects were also included. The second model provided insights on whether funds that exhibit high propensity to buy the recession-proof stock prior to recession are rewarded with superior performance during crisis. The performance measure is represented by the fund's half-year return. Moreover, the model includes set of control variables which represent fund's relevant characteristics as well as year and fund's fixed effects. Both models were subject to additional analysis which aimed to investigate the robustness of the results based on the shorter sample period prior to recession.

The first model was conducted on the pre-recession subsample which consists of 491,121 total transactions made by mutual funds during the period 2005 to the 3rd quarter of 2007. The second model used the pre-recession subsample to obtain the propensity variable which measures the fund's propensity to increase holdings in the recession-proof stock prior to recession. Having the variable computed, the second model was conducted on the recession subsample which includes fund's half-year return and relevant fund's characteristics from the period 2008 to the 2nd quarter of 2009. The abbreviated period used for the additional analysis includes data from the 1st to the 3rd quarter of 2007.

5.2. Conclusions

In conclusion, to answer the stated research question at the beginning of this study: '*Do mutual fund managers hedge against the risk of recession by increasing their fund holdings in the recession-resistant industries?*' The results obtained from the conducted tests lead to the conclusion that the answer, is no.

The analyses that were carried out showed that there is no relation between fund's propensity to increase/decrease holdings in the particular stock prior to crisis and the stock's affiliation to the recession-proof/recession-sensitive industry. Though the additional analysis provides significant results on the fund's buying and selling preferences towards the healthcare stock, the sign of this relationship is opposite to as expected. A possible explanation for these results could be that, as indicated by Treynor and Mazuy (1966) and Henriksson (1984), mutual funds lack market timing ability and, therefore, fail to decrease their portfolio's exposure to the market prior to recession. Another explanation refers to the study of Griffin, Harris, Shu and Topaloglu (2011) which provides evidence that even the most sophisticated market participants like mutual funds or other institutional investors consistently trade in the direction of clear mispricing and base their trading decisions on the mistaken beliefs about future growth opportunities. In this case, the fund managers, despite having superior cognitive resources, might have wrong beliefs about the market dynamics and, hence, ignore or fail to recognize the usual end-of-cycle warnings and do not adjust their trading behavior accordingly. In particular, they fail to decrease their portfolio's market exposure by buying recession-resistant and selling recession-sensitive stock.

Furthermore, the results of the second model do not indicate that the funds which increase their holdings in the recession-proof stock prior to crisis are rewarded with superior performance during economic downturn. Despite controlling for the relevant fund characteristics, this outcome is conflicting with the proposed positive relationship based on the study of Weber (1997) and Bernarke (1981) which imply that companies within recession-proof industries achieve stable performance and employment. A reason for the statistically insignificant relation could be that the data allows to study solely the increase/decrease in the holdings within certain industry during the examined period. Hence, the fund's overall composition of holdings is unknown. Despite the fund having a high increase in their holdings of the recession-proof stock, the fund's portfolio can still consist of other stock that is more sensitive to crisis and, consequently, drag the fund's performance down. Another possible explanation refers to the relevance of the return generated by the recession-proof stock. Although positive, the return generated by the stocks within the recession-resistant sectors might be too small to significantly influence total aggregated fund's return.

5.3. Limitations and avenues for future research

The research design of this study undoubtedly suffers from several data limitations. First limitation refers to the price associated with the transaction of purchase or sale of particular stock. The Thomson Financial CDA/Spectrum database does not provide the stock's price at the moment when the transaction occurred. Instead, the database assigns end of quarter price to the respective transactions. Note that the asset prices are very volatile at the end of the business cycle and price at the moment when the deal occurred might significantly differ from the price at the end of the respective quarter. Such situation can lead to biased value of transaction, especially when the price difference as well as the stock volume is high. Moreover, despite including numerous variables to control for the relevant stock characteristics in the first regression model, ample literature provides evidence for many other relevant factors. For instance, Fang et al. (2014) show that stock's media coverage significantly affects manager's trading decisions (Fang et al., 2014). Other studies stress importance of factors like investing in the companies headquartered nearby (Coval & Moskowitz, 1999, 2001) or in the firms where managers have social connections (Cohen, Frazzini, & Malloy, 2008). All these factors could not be incorporated in the research due to limited data availability. Hence, the coefficient parameters presented in the first model might capture some of the effects that correspond to the unobserved stock characteristics. Lastly, as mentioned in the previous subsection, the second model examining fund's performance suffers from the lack of the data availability on the fund's overall holdings. In particular, the propensity measure is computed by the fund's buys in the healthcare industry before recession and represents exclusively fund's tendency to increase holdings in the healthcare sector, instead of the fund's overall holdings in that industry. Hence, funds that displayed superior tendency to buy the healthcare stock prior to the recession might still hold, relatively to the other funds, small share of their portfolio in the healthcare sector and relatively big share in the industries more sensitive to recession which drags their performance down during economic downturn.

Therefore, the first suggestion for future research refers to examining relation between fund's performance during crisis and its overall holdings in the recession-resistant industries right before recession. Such research design would provide more reliable answer on whether concentration of holdings within more recession-proof sectors is rewarded with superior performance during economic downturn. Another recommendation for future research would be to determine more precisely recession-proof stock. In case of this research, recession-proof stock is determined by the industry associated with the company. However, each firm conducts their business differently and despite not being affiliated with the recession-proof industry, it might display recession-resistant cash-flow and superior performance during crisis. Hence, an opportunity for future study could be to identify such stocks and examine whether mutual funds hedge against the risk of recession by increasing their holdings in them. Finally, the existing literature suggests that actively managed mutual funds achieve superior performance during recessions. However, prior studies provide little suggestions on what exact factors contribute to the extraordinary returns. Therefore, it would be interesting to investigate other possible trading practices which reward mutual funds with superior performance during economic contraction.

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APPENDICES

Appendix A: Trading activity additional analysis

Table 9: Industry classification and trading activity

This table presents panel regression results of mutual fund's trading activity during the adjusted pre-recession period the 1st quarter of 2007 to the 3rd quarter of the same year. The dependent variables are quarterly aggregated fund buys (panel A) and sells (panel B), divided by the fund's total net asset value at the end of the previous quarter. Healthcare/Manufacturing is a dummy variable equaling one if stock belongs to the healthcare/manufacturing industry and zero otherwise. Stock turnover is computed by summing natural log of one with dollar trading volume scaled by the stock's market capitalization at the end of the last quarter. Size represents the market capitalization at the end of the previous quarter, and is measured by the natural log of the stock's market capitalization. Size squared implies the squared size. B/M ratio indicates book-to-market ratio at the end of the earlier quarter. Past return is the decile rank of the stock's return among all the stocks in the sample at the end of the last quarter. Decile of the stocks with the lowest return equals to one, and decile of the stocks with the highest return is ten. Quarter and fund fixed effects incorporate the fixed effects to the corresponding quarters and funds respectively. OLS robust standard errors are presented in the parentheses below the coefficient parameters. *, **, and *** imply significance level at the 10%, 5%, and 1%, respectively.

Panel A: Buys/TNA				
	Panel A: Buys/TNA		Panel B: Sells/TNA	
	(1)	(2)	(3)	(4)
Healthcare	-0.0025*		0.0042**	
	(0.0015)		(0.0021)	
Manufacturing		-0.0037***		0.0012
		(0.0014)		(0.0019)
Controls				
Stock turnover	0.0036***	0.0035***	0.0038***	0.0037***
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Size	-0.0109***	-0.0104***	-0.0014	-0.0019
	(0.0025)	(0.0025)	(0.0045)	(0.0045)
Size squared	0.0009***	0.0009***	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
B/M ratio	-0.0028	-0.0020	0.0129***	0.0117**
	(0.0018)	(0.0017)	(0.0045)	(0.0050)
Past return	0.0003	0.0003	0.0007**	0.0006**
	(0.0001)	(0.0002)	(0.0003)	(0.0003)
Quarter fixed effects	yes	yes	yes	yes
Fund fixed effects	yes	yes	yes	yes
Constant	0.0088	0.0069	-0.1015***	-0.0974***
	(0.0083)	(0.0085)	(0.0246)	(0.0246)
Observations	72,218	72,218	49,222	49,222
R^2	0.636	0.636	0.494	0.494
Adjusted R^2	0.630	0.630	0.483	0.483

Appendix B: Propensity and latter performance additional analysis

Table 10: Trading activity and fund performance

This table reports panel regression results on fund's propensity to buy healthcare stock and future performance based on the sample from 2008 to the 2nd quarter of 2009.The dependent variable is fund's half-year return. Propensity is the decile rank of fund's propensity to increase holdings in healthcare industry during the pre-recession period from the 1st quarter of 2007 to the 3rd quarter of the same year. For each fund, the increase/decrease in holdings is calculated by calculating the difference between the total dollar value of buys and sales and, then dividing the difference by the fund's average TNA from 2007. The rank of funds that decreased their holdings or did not trade the healthcare stock at all is 0; the remaining funds are assigned to the respective quantiles where 1 indicates the funds that increased their holdings the least, and 7 represents the funds that increased their holdings the most. Expense is the fund's expense ratio. Turnover is the fund's annual turnover. Fund size is the natural log of one and fund's TNA. Age is the natural log of years since when the fund was first offered. All the control variables are lagged by one year. OLS robust standard errors are presented in the parentheses below the coefficient parameters. *, **, and *** imply significance level at the 10%, 5%, and 1%, respectively.

	Coef.	*t*-stat
Propensity	-0.0363	-0.88
	(0.0410)	
Controls		
Expense	-0.6824	-0.42
	(1.6429)	
Turnover	0.0170	0.80
	(0.02114)	
Fund size	-0.0101	-2.29**
	(0.0044)	
Age	-0.0014	-0.14
	(0.0102)	
Year fixed effects	yes	yes
Fund fixed effects	yes	yes
Constant	-0.0964	-1.56
	(0.0618)	
Observations	2,559	
R^2	0.595	
Adjusted R^2	0.338	