The 99% Market Sentiment Index

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ABSTRACT

We build a market sentiment index based solely on the changes over time in the number of different stocks held by individual investors. No prices, returns or trading volumes enter the definition and trades of unwealthy and underdiversified investors are overweighted in our sentiment index. Using the trades and portfolios of a large sample of 87,373 French investors over a eight-year period, we show that our index outperforms other usual indices (based on surveys, macro-economic variables or buy-sell imbalances) in predicting short-term returns on long-short portfolios based on size or on the book-to-market ratio. An increase of one standard deviation of our market sentiment index in a given month implies a decrease of 1.05% of the return on such a long-short size based portfolio the following month. A simple dynamic strategy driven by our sentiment index delivers a Sharpe ratio higher than that of random dynamic strategies in 99.6% of cases and a much higher Sharpe ratio than the one of a buy-and-hold strategy.

Introduction

On September 17, 2012, Occupy Wall Street was celebrating the first anniversary of its movement. People demonstrating in New York City had stickers on their T-shirts saying “We are the 99%”. This slogan implicitly referred to the 1% of investment bankers, fund managers, and more generally finance professionals. In short, “We are the 99%” excludes all the investors who “make the market”. The 99% is made up of the other people who are the “market takers”. Among these market takers, individual investors are

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often identified as noise traders because they trade on noise as if it were information (Black, 1986). In this paper we show that the transactions of the so-called "noise traders" convey valuable information when it comes to measuring market sentiment and to predicting future returns. We show that the dynamics of diversification choices of unwealthy and underdiversified investors are not noisy in the sense that these dynamics reveal market sentiment[2].

Our market sentiment index (henceforth *MSI*) aggregates changes in portfolio diversification in an original way because our *MSI* depends solely on the variation of the number of *different* stocks in individual portfolios. In particular, no prices, returns or trading volumes enter the definition. As a consequence, our measure *MSI* is not contaminated by liquidity concerns present in measures based on buy-sell imbalances. However, it does not mean that the level of *MSI* is independent of market liquidity because one may argue that individual investors trade more when the market is liquid and the transaction costs are low, whatever the precise measure of liquidity is used. Our empirical study addresses this issue.

Our starting points are two well-documented traits of individual investors. First, they hold underdiversified portfolios[3] and second, their decisions are narrowly framed. According to Kumar and Lim (2008), the more an investor is underdiversified, the more she frames narrowly her decisions. As a consequence, an underdiversified investor with only a few thousand dollars to invest in the stock market signals her optimism[4] about future prices when she buys a new stock (that is a stock not already held). The decision to buy is evaluated in isolation, separately from the other (two or three) stocks in the portfolio.

The definitions of sentiment in the literature are diverse, but mainly *sentiment* aggregates what is not explained by fundamentals. Our idea in this paper is that changes in diversification levels of underdiversified investors should be driven more by sentiment than by fundamentals. Moreover, we conjecture that the sentiment revealed by the trades of the 99% is not

2. Investor sentiment is a hot topic in current research according to the number of papers published recently (Mendel and Shleifer 2012, Stambaugh *et al.*, 2012, Ben-Rephael *et al.*, 2012, Baker *et al.*, 2012)

3. Lease *et al*. (1974) and Blume and Friend (1975) were the first to highlight the portfolio underdiversication of retail investors followed by Kelly (1995). More recently, a number of empirical studies (Odean 1999, Mitton and Vorkink 2007, Goetzman and Kumar 2008) provide the same results on large samples of U.S. individual investors. Calvet *et al*. (2007), Roger *et al*. (2013) obtain similar patterns for the Swedish and French markets.

4. Barberis *et al.* (2006) show that narrow framing allows to explain why people often reject small actuarially favorable gambles.

different of the sentiment of the 1%. Because the trades of the 1% are often constrained by management or regulatory rules, it is easier to extract a measure of sentiment from the trading activity of the 99%. Therefore, our argument in this paper is not to say that trades of individual investors move prices and returns due to a demand/supply effect, but that the trades of these small investors convey more information about sentiment (and probably less about fundamentals) than the trades of finance professionals.

The only input needed to calculate our sentiment index in a given month is the variation of the number of *different* stocks in individual investors' portfolios. In fact, we describe the dynamics of the number N of *different* stocks in portfolios as a Markov chain and characterize the steady-state equilibrium of the stochastic process N. Our sentiment index is the area below the decumulative distribution function of the steady-state equilibrium number of stocks in portfolios. Due to properties of decumulative distribution functions, our index is proportional to the expected number of stocks held by investors in the steady-state equilibrium.

The empirical study shows that our index outperforms the other usual sentiment measures in explaining future returns of some long-short portfolios based on the "sentiment seesaw" of Baker and Wurgler (2007). These authors show that sentiment can have opposite effects on stock returns, depending on the difficulty of engaging in stock arbitrage. In high-sentiment periods, large/value stocks may be undervalued and small/distressed stocks may be overvalued. The reverse appears in low-sentiment periods. Therefore, a zero-cost long-short portfolio with a long (short) position on large market capitalizations and a short (long) position on small capitalizations when sentiment is high (low) should generate abnormal returns. As a consequence, regressing the returns of these long-short portfolios on a sentiment measure should result in a negative regression coefficient. It is the case for all sentiment measures we test in this paper but the *MSI* outperforms the other measures in terms of statistical and economic significance. This is the case either in simple regressions or when we control for the market factor, the Fama-French factors, the momentum Carhart factor, and finally the market illiquidity factor defined as the percentage of zero daily returns as in Lesmond[5] *et al.* (1999). As a result, an increase of one standard deviation of the *MSI* (which is equal to 0.21 over the period under consideration) in

5. In the remainder of the paper, the liquidity factor is denoted LOT factor for Lesmond-Ogden-Trzcinka.

a given month generates a decrease of 1.05% of the return on the above-mentioned long-short size-based portfolio the following month[6].

Our sentiment measure has two main advantages beyond the fact that it is a measure free from liquidity concerns. First, trading volume does not take part in the definition it enables the disentanglement of the effect of sentiment from a potential demand/supply effect of retail trades. Second, a well-known result in Markov chain theory says that the steady-state equilibrium distribution of the stochastic process *N* is independent of the current state. This result indicates that our measure of sentiment for month *t* does not depend on the diversification levels of investors at the beginning of the month, instead depending only on the transition matrix of the Markov chain of month *t*. This property means that our index can be used to implement dynamic investment strategies without any econometric estimation from time-series. It is not the case for all sentiment measures.

Sentiment measures can be divided into three categories. The first category consists of measures deduced from answers to questionnaires (related to expectations). The index of consumer sentiment (*ICS*) provided by the university of Michigan is a well-known example (Lemmon and Portniaguina, 2006). In our empirical study, we use the French consumer confidence index (henceforth *FSI*), the construction of which is close to that of the *ICS*.[7] These two indices essentially measure consumer confidence, as they are related to expectations regarding economic conditions or future financial wealth. Other survey-based indices such as the index of the American Association of Individual Investors (AAII) and the index of Investors Intelligence (II), are more focused on financial markets. These indices estimate the bullish/bearish spread, with the AAII index focusing on individual investors and the II index focusing on writers of financial newsletters. Brown and Cliff (2004) link these indices to a number of sentiment-related variables but also show that they have no significant predictive power for market returns.

The second category of sentiment indices consists of top-down measures, which are based on macroeconomic variables. Baker and Wurgler (2006) define a sentiment index as a linear combination of six variables: the closed-end fund discount, the logarithm of the NYSE share turnover ratio (detrended by the 5-year moving average), the number of IPOs, the

6. The regression coefficient of the lagged sentiment measure is –0,051.

7. See Appendix 2 for a short description of the two indices ICS and FSI.

average first-day return on IPOs, the share of equity issues in total equity and debt issues and the dividend premium, defined as the log difference in the average market-to-book ratios between dividend payers and non-payers. The sentiment measure is chosen as the first principal component of a Principal Component Analysis of the six variables. Baker and Wurgler (2006) also define an orthogonalized version of their sentiment index by first regressing each of the six variables on growth in the industrial index, growth in consumer durables, non-durables and services and a dummy variable for NBER recessions. The authors then consider the inputs of the PCA as the residuals of these regressions to define the orthogonalized version of their sentiment index. We do not consider this orthogonalized measure in our comparison because it suffers from a look-ahead bias. Moreover, the results would be very close for the two Baker-Wurgler indices.

Finally, the third category of measures relates to buy-sell imbalances. If a category of investors (individual or institutional) can reveal the market sentiment, measuring the buy-sell imbalance of this category may be a good measure of sentiment[8]. The imbalance can also be considered between categories of investors. For example, Edelen *et al.* (2010) propose a measure of relative sentiment based on the differences in allocations between retail investors and institutional investors.

Our *MSI* differs from survey-based measures because survey-based indices measure what people think about future financial and economic conditions but do not control for what people actually do. Our measure also differs sharply from the Baker-Wurgler index because we do not require a long time-series of past data to estimate the current value of market sentiment. Only some current trades made by individual investors are relevant. Therefore, the principal competitor of our index is the buy-sell imbalance measure. The main difference between the two is that we use much less information to build our measure and that, as we demonstrate below, the predictive power of our measure is much stronger. It possibly looks like a paradox, but taking into account all trades in buy-sell imbalance measures introduces noise when the point is to measure market sentiment.

In order to validate the *MSI*, we build a time-series of the index using trading records and portfolios of a large sample of 87,373 French individual

8. For example Kumar and Lee(2006), Schmitz *et al.* (2007), Andrade *et al.* (2008), Hvidkjaer (2008), Barber and Odean (2008), Kaniel *et al.* (2008), Barber *et al.* (2009) use buy-sell imbalance measures either to measure sentiment or to analyze correlated trading among individual investors.

investors over the period 1999-2006. The other sentiment indices are selected in the three abovementioned categories: the French consumer sentiment index published by National Institute of Statistics and Economic Studies[9], the Baker-Wurgler index and the Buy-Sell imbalance measure (*BSI*).

Our main empirical results are the following.

1) We use a two-step methodology to test the predictive power of sentiment indices. In a first step, we regress the returns of long-short portfolios (based on size or on the book-to-market ratio) on the lagged sentiment index. In a second step, we control for the market factor and the four Fama-French-Carhart-LOT factors. As predictors can be autocorrelated, the regression coefficients are biased. We therefore use the Amihud-Hurvich (2004) bias-reduction technique. The results show that our *MSI* is always statistically significant and delivers the highest adjusted $\overline{R}^2$ in the uncontrolled and controlled regressions for size portfolios and in uncontrolled regressions for book-to-market portfolios. It also appears that the buy-sell imbalance index (*BSI*) is outperformed by the *MSI* in both cases, despite the fact that the *MSI* "neglects" trades that do not change diversification levels.

2) Building on the predictive power, we test a simple investing strategy of heavily buying the market index when the *MSI* is high in the preceding month. In 99.6% of cases, the Sharpe ratio of this dynamic strategy is higher than the Sharpe ratio of the uninformed strategies where the proportion invested in the market index is drawn at random between 0 and 100%. Moreover, the Sharpe ratio is much higher than that of a buy-and-hold strategy.

3) The performance of the *MSI* is robust to variations in the minimum portfolio value of investors included in the database and in the number of states of the Markov chain used to model the number of stocks in portfolios. Including constraints to keep only portfolios worth more than 1,000 € or 5,000 € does not change the results, except when the number of states is too low. We explain this fact in the empirical section. We also illustrate in this section that our sentiment index is not significant in the prediction of "long-term" returns. This result is consistent with the way we built the index. For example, trying to predict portfolio returns for the first semester of 2015 with the *MSI* of December 2014 means that we voluntarily neglect the information coming in January, February, etc.

9. INSEE: Institut National de la Statistique et des Etudes Economiques.

The remainder of the paper is organized as follows. Section 1 describes the diversification dynamics as a Markov chain and shows that trading conditions allow for the existence of a steady-state equilibrium. Then we define our market sentiment index after having illustrated the intuition behind this approach with an example. Section 2 presents the data and some descriptive statistics. Section 3 contains the main empirical results and section 4 provides several robustness checks. A final section concludes.

1. The model

1.1 The Markov chain of diversification levels

We assume that K stocks are traded in the market by I investors. The market is open at dates $t = 1,2, \ldots, T$. As mentioned in the introduction, we know the composition of portfolios of individual investors at given points in time (on a monthly basis in this paper). We are then able to evaluate the variation of the number of different stocks in their portfolios between dates t and $t+1$, for $t = 0$ to T ($t = 0$ is the beginning of 1999 and $t = T$ corresponds to December 2006).

Let N_t^i denote the number of different stocks held by investor $i \in \{1, \ldots, I\}$ at date t (the beginning of month t in the empirical study). N_t^i can be seen as a random variable taking values in the set $\{1, \ldots, K\}$.

Q_t^i stands for the one-period transition probability matrix of the stochastic process $\left(N_t^i, t = 0,\ldots,T\right)$. It is defined by:

$$\forall 1 \leqslant k \leqslant K, \forall 1 \leqslant m \leqslant K, Q_t^i(k,m) = P\left(N_{t+1}^i = m \middle| N_t^i = k\right) \qquad (1)$$

$Q_t^i(k,m)$ is the probability that the portfolio of investor i contains m different stocks at date $t+1$, given her having held k different stocks at date t. From now on, we assume that investors are homogeneous in the sense that $Q_t^i = Q_t$ for all $i \in \{1, \ldots, I\}$. All lines in Q_t sum to 1, by construction of the transition probability matrix of a finite Markov chain. For the empirical analysis to follow, we assume that K is not too large ($K = 20$ in the typical case). State K receives all portfolios with a number of different stocks greater than or equal to K.

The structure of Q_t provides an idea of the dynamics of portfolio diversification between t and $t+1$. It is important to note that Q_t does not carry any specific information about trading volumes, prices, returns or which stocks are traded. Roughly speaking, if the terms above the diagonal of Q_t are greater than those below the diagonal, we expect an increase in the mean number of stocks in portfolios over time. If the opposite is true, the portfolio of the investor should be more concentrated (containing a lower number of different stocks) in future periods. The measure of diversification we use is then quite simple.

Other measures of diversification have been used in the literature, such as the Herfindahl index of weights in the portfolio (Mitton and Vorkink, 2007) or the normalized portfolio variance, which is defined as the ratio of the portfolio variance to the mean variance of stocks in the portfolio (Goetzmann and Kumar, 2008). These alternatives may also be used to test our model but would require the (potentially arbitrary) definition of ranges of diversification levels to categorize investors and build the transition probability matrix. Moreover, such measures would not be completely consistent with our interpretation in terms of sentiment. In fact, we stated earlier that buying new stocks reveals optimism, but a change in the normalized portfolio variance or in the Herfindahl index does not mean that investors change something in their portfolio. A variation in these measures may simply appear because stock prices move over time.

If Q_t signals the optimism/pessimism of investors between dates t and $t+1$, a natural question is to know what the portfolios would be in the long-run if investor sentiment remained stable over time, that is if Q_t remained unchanged over time. The answer to this question is easily obtained under mild technical conditions, thanks to the properties of homogeneous Markov chains[10].

1.2 Steady-state equilibrium of diversification levels

Homogeneous Markov chains have a nice property: it is possible to find a steady-state equilibrium that is a vector $\pi' = (\pi_1, \ldots, \pi_k)$ such that π_k is the proportion of investors holding k stocks in the long run. However, for the vector π to exist, the following two conditions have to be satisfied.

Denote $Q_t^{(n)}$ the n-period transition matrix defined by:

$$Q_t^{(n)}(k,m) = P(N_{t+n} = m | N_t = k) \text{ for } (k, m) \in \{1, \ldots, K\}^2.$$

10. A Markov chain is said homogeneous if Q_t does not depend on t.

1. The Markov chain is irreducible. It is the case if for each pair (*k, m*) there exists *n* such that $Q_t^{(n)}(k,m) > 0$. It is generally said that *k* and *m* communicate.

2. The Markov chain is aperiodic. Denote $R(k) = \{n \in \mathbb{N}^*$ such that $Q_t^n(k,k) > 0\}$ the set of return times of state *k*. The period of *k*, denoted by $p(k)$, is the greatest common divisor of the numbers in $R(k)$. The chain is said aperiodic if $p(k) = 1$.

Conditions (1) and (2) are satisfied in our case because individual investors can buy new stocks or they can sell the stocks they hold without regulatory constraints.

Q_t being assumed identical for all investors, the elements of Q_t are estimated by:

$$Q_t(k,m) = \frac{\sum_{i=1}^{I} 1_{\{N_{t+1}^i = m\} \cap \{N_t^i = k\}}}{\sum_{i=1}^{I} 1_{\{N_t^i = k\}}} \qquad (2)$$

where 1_A is the indicator of the event *A*, valued 1 if *A* is true and 0 otherwise.

The specific properties of Markov chains allow to evaluate the two-period transition matrix. Denoting as before $Q_t^{(2)}(k,m) = P(N_{t+2} = m | N_t = k)$, the Chapman-Kolmogorov equations imply:

$$Q_t^{(2)} = Q_t \times Q_t = Q_t^2 \qquad (3)$$

More generally, the *n*-period transition probability matrix satisfies $Q_t^{(n)} = Q_t^n$. The steady-state equilibrium is given by any line of the limit matrix $\lim_{n \to +\infty} Q_t^n$ (all lines of this matrix are equal).

1.3 An illustration

As an illustration of the above results, we provide hereafter the successive powers of two different (5,5) transition matrices *Q* and *Q**. The first one on the left of table 1 characterizes "optimistic" or high-sentiment investors and the second one on the right more "pessimistic" investors.

Table 1. This table gives the powers 1, 4 and 8 of the (5,5) transition matrices Q ("more optimistic") and Q^* ("less optimistic"). The first column (line) gives the number of stocks at date $t(t + n)$.

	Q^n					Q^{*n}				
	Power: $n = 1$									
Nb stocks	1	2	3	4	5	1	2	3	4	5
1	0.500	0.200	0.100	0.100	0.100	0.500	0.200	0.100	0.100	0.100
2	0.050	0.600	0.200	0.100	0.050	0.150	0.600	0.100	0.100	0.050
3	0.100	0.100	0.500	0.200	0.100	0.100	0.200	0.500	0.100	0.100
4	0.050	0.100	0.150	0.500	0.200	0.100	0.150	0.200	0.500	0.050
5	0.05	0.100	0.150	0.150	0.550	0.050	0.100	0.150	0.200	0.500
	Power: $n = 4$									
Nb stocks	1	2	3	4	5	1	2	3	4	5
1	0.143	0.245	0.226	0.204	0.182	0.199	0.293	0.197	0.182	0.129
2	0.107	0.265	0.249	0.210	0.168	0.189	0.324	0.194	0.177	0.116
3	0.117	0.208	0.247	0.230	0.198	0.174	0.293	0.223	0.182	0.129
4	0.105	0.202	0.233	0.239	0.221	0.174	0.285	0.220	0.203	0.118
5	0.105	0.202	0.233	0.224	0.236	0.156	0.262	0.219	0.208	0.155
	Power: $n = 8$									
Nb stocks	1	2	3	4	5	1	2	3	4	5
1	0.114	0.225	0.239	0.222	0.200	0.181	0.296	0.208	0.188	0.126
2	0.113	0.225	0.240	0.223	0.199	0.182	0.298	0.208	0.187	0.126
3	0.113	0.222	0.239	0.224	0.203	0.181	0.296	0.209	0.188	0.126
4	0.112	0.221	0.239	0.224	0.204	0.181	0.296	0.209	0.188	0.126
5	0.112	0.221	0.239	0.224	0.204	0.179	0.295	0.210	0.189	0.127

We provide the powers 1, 4 and 8 of the two matrices to illustrate the convergence process. Q (Q^*) is said "optimistic" (pessimistic) because, roughly speaking, the probabilities of increasing (decreasing) the number of stocks are higher than probabilities of decreasing (increasing) this number. When directly examining matrices Q and Q^*, it may appear difficult to detect which matrix leads to an increase (decrease) in diversification in the long run. However, recall that transition matrices are evaluated with equation (2). A simple indicator of whether diversification increases is the ratio of the number of investors above the diagonal divided by the total number of investors. Suppose that in our example there are 10,000 investors in each of the five lines of Q and Q^*. The numbers in Q show that 5,000 single-stock holders at date t increase the number of stocks they hold at date $t+1$. The second line shows 3,500 investors increasing diversification. Globally, 16,500 investors increase diversification between the two dates that is 33% of the total number of investors in the sample. For Q^*, the same calculation shows only 10,000 investors (20%) increasing diversification.

Even for $n = 8$, we observe that the steady-state equilibrium is not reached yet because slight variations still appear across lines. In fact, the true equilibrium distribution leads to 11.3% of investors with only one stock, 22.3% with two stocks, and so on. Regarding Q^*, the initial matrix is not so different from Q but probabilities of decreasing the number of stocks are higher on average. The long-run consequence of these differences is that the steady-state equilibrium shows 18.1% of single-stock owners, 29.6% of investors with two stocks, and so on.

The long-run equilibrium proportions (denoted by π and π^*) are equal to:

$$\pi = (0.113; 0.223; 0.239; 0.223; 0.202) \qquad (4)$$
$$\pi^n = (0.181; 0.297; 0.209; 0.188; 0.126) \qquad (5)$$

The cumulative distribution functions (CDF) of π and π^*, denoted by F and F^*, are then given by:

$$F = (0.113; 0.336; 0.575; 0.798; 1) \qquad (6)$$
$$F^* = (0.181; 0.478; 0.687; 0.855; 1) \qquad (7)$$

The two corresponding decumulative distribution functions $1 - F$ and $1 - F^*$ are plotted on figure 1. The bold (dashed) line represents the pessimistic (optimistic) distribution. The optimistic distribution F first-order stochastically dominates the other one as $1 - F$ is always above $1 - F^*$. It means that transitions induced by Q lead to more diversified portfolios than those driven by Q^*. According to these curves, a reasonable measure of market optimism (pessimism) is the area below the decumulative distribution function. We will keep this way of measuring the market sentiment index, denoted by *MSI*. To normalize the index between 0 and 1, we divide the area by the maximum number of stocks K minus 1. In this example, we get the following values:

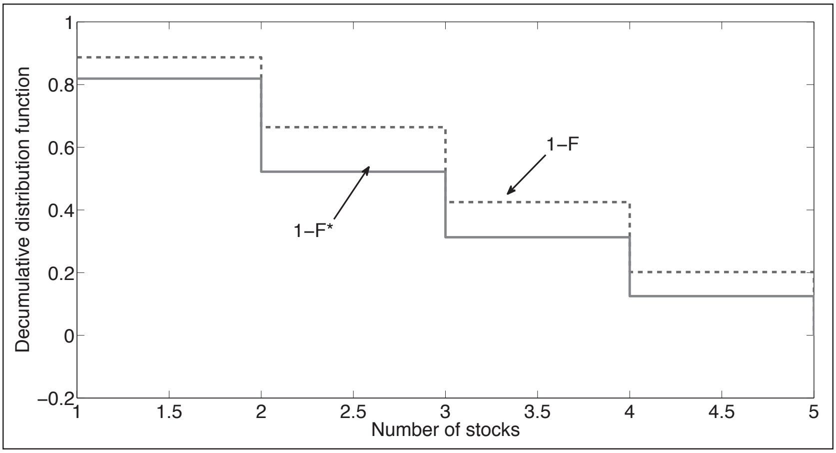
$$MSI = \frac{1}{4}[(1-0.113)+(1-0.336)+(1-0.575)+(1-0.798)] = 0.5445$$

$$MSI^* = \frac{1}{4}[(1-0.181)+(1-0.478)+(1-0.687)+(1-0.855)] = 0.4498$$

The fact that $MSI > MSI^*$ comes from the relationship between Q and Q^* (Q is more optimistic than Q^*). In the next section, we demonstrate the causality of this relationship in a general framework.

In the empirical analysis, each transition matrix Q_t estimated with diversification changes between $t = 1$ and t allows calculating an equilibrium distribution F_t, and consequently the market sentiment index MSI_t.

Figure 1. Decumulative long-run distribution functions 1 – *F* and 1 – *F** corresponding to transition matrices *Q* (dashed line) and *Q** (bold line).



1.4 A formal definition of the market sentiment index (MSI)

We are now ready to define our sentiment index in a more formal way as the area below the decumulative distribution function of the equilibrium number of different stocks in the portfolio.

Definition 1. *For a transition matrix* Q_t *between* $t-1$ *and t, denote* $N_{\infty,t}$ *the random variable "number of different stocks" in the steady-state equilibrium. The investor sentiment index MSI is defined by:*

$$MSI_t = \frac{1}{K-1}\sum_{k=1}^{K-1} P(N_{\infty,t} > k) \qquad (8)$$

As said before, MSI_t simply measures the area below the decumulative distribution function of $N_{\infty,t}$ It is important to remind that the essential feature of the convergence theorem of Markov chains is that the steady-state equilibrium does not depend on the initial distribution of investors. In particular, this property means that, Q_t being given, we do not need to know the composition of the sample of investors between single-stock holders, two-stock holders and so on, to evaluate the sentiment index. Only the changes between $t-1$ and t are important. Of course, the transition matrix Q_t may depend on the distribution of investors at $t-1$. Intuitively, the probability of decreasing diversification differs between investors holding 3 stocks and those holding 30 stocks.

The second property of the index is recalled in the following lemma.

Lemma 2. $MSI_t = \frac{1}{K-1}\sum_{k=1}^{K-1} P(N_{\infty,t} > k) = \frac{1}{K-1}\left(E(N_{\infty,t}) - 1\right)$

This lemma simply recalls that the integral of the decumulative distribution function of a random variable is equal to its expectation. It is very useful to show that definition 1 is consistent with the intuition developed in the illustration of section 3. The intuitive idea is that if elements above the diagonal are larger in Q than in Q^*, the resulting sentiment measure should be higher in "world Q" than in "world Q^*", because the probability of increasing the number of different stocks is higher. The following proposition demonstrates the consistency of our definition.

Proposition 3. *Let us denote* N_t (N_t^*) *the number of stocks in portfolios at date t when the transition matrix is* Q (Q^*) *with* $Q = Q^* + \Delta$ *and* Δ *satisfying:*

$$\forall (j,k) \in \{1,...,K\}^2, k > j \Rightarrow \Delta_{jk} \geqslant 0 \qquad (9)$$

$$\forall j \in \{1,...,K\}, \sum_{k=1}^{K} \Delta_{jk} = 0 \qquad (10)$$

We then have:

$$MSI \geqslant MSI^* \qquad (11)$$

where *MSI* (*MSI**) is the sentiment index calculated with transition matrix $Q(Q^*)$.

Proof. The proof is reported in Appendix 1.

The transition matrix Q_t contains useful information. For example, it has been observed during long bullish high-sentiment periods (such as the dotcom bubble), that more and more investors enter the market and that those already in the market increase their stakes and invest in new stocks, thus increasing diversification[11]. In such situations, the elements above the diagonal of the transition matrix increase over time.

Roughly speaking, $Q_t(k, m) > Q_t(m, k)$ in bullish markets. In bearish markets or recession periods, investors are reluctant to put new money on the table and may sell stocks to finance consumption or liquidity needs. Consequently, we expect $Q_t(k, m) \leqslant Q_t(m, k)$ in bearish markets. However, some asymmetry may arise; in fact, at the individual level, a decrease in diversification does not always reveal pessimism. It is well known that individual investors are prone to the disposition effect, selling winners too early and riding losers for too long[12]. Therefore, it may happen that bearish markets induce some inertia in the transition matrix, where investors maintain a position in their losing stocks. It turns out that the time-series of the terms on the diagonal of Q may be a good indicator of pessimism.

1.5 Buy-Sell imbalance

For a given stock i, the buy-sell imbalance index in month t is defined by:

$$BSI_{it} = \frac{\sum_1^{d_t} (B_{it} - S_{it})}{\sum_1^{d_t} (B_{it} + S_{it})} \qquad (12)$$

where d_t is the number of trading days in month t, $B_{it}(S_{it})$ is the volume of buying (selling) trades for stock i in month t.

To define the buy-sell imbalance (*BSI*) of a portfolio, we can either average the *BSI* of the stocks in the portfolio (see for example Kumar and

11. Goetzmann and Kumar (2008) point out an increase in the average number of stocks held by investors in a large sample of U.S investors over the period 1991-1996 (the market was almost always bullish during this period). From 4.28 in 1991, it rises to 6.51 in 1996. The authors do not attribute this variation to an increase in financial skills of retail investors.

12. The disposition effect is one of the well-documented biases of individual investors. It has been first studied by Shefrin and Statman (1985). A number of empirical studies in several countries show that individual investors are prone to the disposition effect (Odean (1998) in the U.S, Shapira and Venezia (2001) in Israel, Barber *et al.* (2007) in Taiwan, Boolell-Gunesh *et al.* (2009) in France).

Lee, 2006) or we can aggregate buy and sell trades on stocks in the portfolio. In this paper, following Barber and Odean (2008), we choose the latter solution and define the market *BSI* by:

$$BSI_{Mt} = \frac{\sum_{i=1}^{N_t} \sum_{1}^{d_t} (B_{it} - S_{it})}{\sum_{i=1}^{N_t} \sum_{1}^{d_t} (B_{it} + S_{it})} \qquad (13)$$

where $B_{it}(S_{it})$ is defined as before and N_t is the number of different stocks traded in month t.

We prefer the definition given in equation 13 because we focus on a market sentiment index, not on stock-level sentiment indices. Given the trade frequency of investors in our database, 25 % to 30 % of stocks are traded each month; consequently the stock *BSIs* cannot be defined for every stock every month. It justifies the way we calculate the aggregate buy-sell imbalance index. As usual, when comparing means of ratios and ratios of means, the difference between the two quantities is increasing in the cross-sectional variation of the stock-level *BSIs*.

Moreover, being consistent in our comparison with the other indices, especially *MSI*, requires to cumulate (in a month t) only the trades of investors who are still in the database the day after they trade. In fact, when investors close their accounts, we do not know why. Maybe they simply change their broker or maybe they need money to buy a house or their preceding losses convince them to give up investment in stocks.

2. Data and descriptive statistics

2.1 Investors data

Data on individual investors come from a large French brokerage house. A detailed presentation of this database has already be given in Boolell-Gunesh *et al.* (2009)[13]. We obtained transaction data for all active accounts over the period 1999-2006, amounting to a total of 9 million trades among 92,603 investors. Two different files were used in the present paper. First, the trades file gives the following information for each trade: the ISIN code of the asset, the buy-sell indicator, the date, the quantity and the amount in Euros. Second, the investors file compiles some demographic characteristics

13. Part of the database was also used in Boolell-Gunesh *et al.* (2012) and in Merli and Roger (2013).

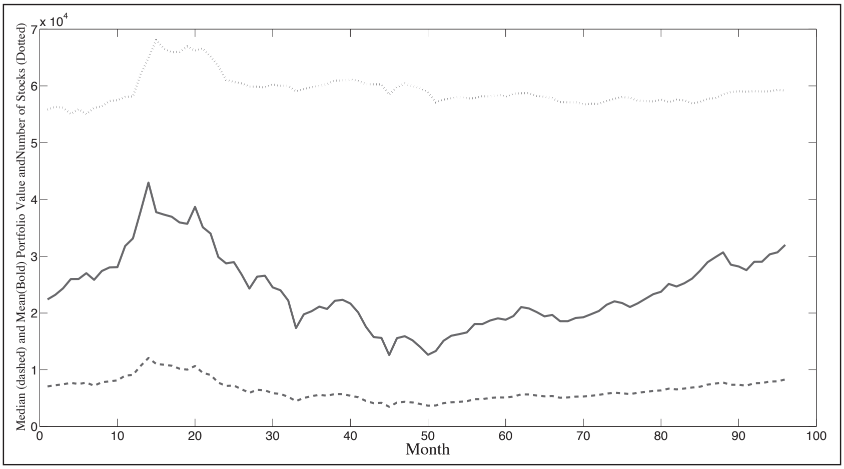
of investors: date of birth, gender, date of entry to and exit from the database, opening and/or closing dates of all accounts and region of residence.

Some investors open an account during this period, and some others close their account before the end of this period. Because it would make no sense to analyze portfolios every day (due to the low turnover of portfolios), we chose to "take a photograph" of portfolios at the end of each month. We found that some investors may hold no position in a given month when they previously held a portfolio, and restart trading later. We removed from the sample investors with positions in stocks for which price data were not available for at least one year and those with portfolios worth less than 100 €. Finally, 87,373 investors were considered in the analysis (they held stocks for at least two consecutive months during the period under study) but their number varies over time. 8,258,809 trades remain in our final database. On average, 51,340 investors hold a position in a given month (with a minimum of 34,230 and a maximum of 60,001).

Figure 2 shows three time-series. The upper dotted curve represents the average number of stocks held by investors ($\times 10^4$). We observe that underdiversification is more the rule than the exception, as the average number of stocks varies from 5.5 to 6.8, and the median is 3 or 4 all over the period. The difference between the median and the mean is explained by a low percentage of investors holding largely diversified portfolios. These figures are in line with those obtained in the studies referred to in the introduction. It is then reasonable to postulate that individual investors hold underdiversified portfolios and that buying a fourth stock when three are already in the portfolio does not have the same effect as buying a new stock when the portfolio is already fully diversified with 200 stocks. The striking feature of this curve is the sharp increase in the average number of stocks just before the dotcom bubble burst, that is, during the first months of 2000. A decrease to the former level of diversification is observed in the subsequent period. For the remainder of the period, the average number of stocks is roughly stable. This curve also shows that considering the average change of diversification would not yield enough information to measure market sentiment. For this reason, we use Markov chains to better extract information about sentiment. The evolution of the number of stocks is different from that observed by Goetzman and Kumar (2008) on a sample of U.S. investors. As mentioned before, they found an increase in diversification over the period 1991-1996 because the market was bullish almost all the time during this period.

The middle bold curve and the bottom dashed curve provide the evolution of the mean and median portfolio values. With the first month set as January 1999, it appears that the average portfolio value follows the evolution of the market as a whole. A sharp increase in value appears in the first 15 months, up to the bursting of the Internet bubble in April 2000. Then, portfolio values decrease until April 2003 (the bottom of the market), and a partial recovery is observed between 2003 and the end of our period (December 2006). Consequently, the evolution of portfolio values in our sample does not appear to differ from the evolution of the stock market as a whole.

Figure 2. Monthly average number of stocks (dotted curve x10,000), mean portfolio value (bold curve) and median portfolio value (dashed curve) over January 1999-December 2006.



With regard to the number of stocks in portfolios, there is also a large discrepancy between the mean and median portfolio values, a result in line with other studies on individual investors (for example Mitton and Vorkink, 2007). In fact, a few investors are very wealthy compared to the average investor; these investors drive up the average portfolio value. On average, 0.2% of investors hold a stock portfolio worth more than 1,000,000 €.

Table 2. Statistics on portfolio values at three points in time, April 2000 (Panel A), April 2003 (Panel B) and April 2006 (Panel C). The first column gives the way portfolios are categorized with respect to the number of stocks. Portfolios containing 6 to 9 stocks are in the same category and portfolios with more than ten stocks are also grouped. The second column shows the number of investors in each diversification group. The four last columns describe portfolio values by providing the mean portfolio value, the first quartile, the median and the third quartile.

Portfolio Value (€)					
Portfolio Size	Nb. of Observations	Mean	25^{th} percentile	Median	75^{th} percentile
Panel A: Portfolios as of April 2000					
1	8376	7257	728	1666	4217
2	6589	10537	1918	3747	8010
3	5478	14478	3340	6014	12404
4	4426	20635	4973	8771	16839
5	3587	23696	6513	10842	20534
6-9	9315	38513	10302	17911	33273
10+	10760	101748	26330	47367	90474
All	48531	37902	3714	10921	30493
Panel B: Portfolios as of April 2003					
1	13533	2219	227	519	1341
2	9137	3564	686	1387	3036
3	6812	5791	1255	2409	5003
4	5246	7161	1945	3561	7011
5	4079	9810	2782	4955	9576
6-9	9925	15228	4677	8181	15088
10+	10044	40800	12494	22583	42157
All	58776	12600	1056	3531	10964
Panel C: Portfolios as of April 2006					
1	10778	4409	427	1105	2993
2	7248	8749	1395	3058	6914
3	5224	13598	2663	5488	11968
4	4090	18915	4278	8005	16664

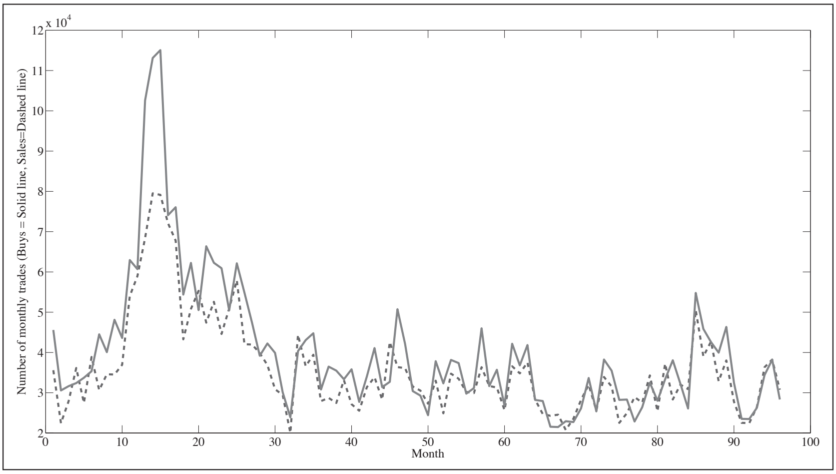
5	3253	23800	5773	10864	21500
6-9	7759	35751	9864	18040	35316
10+	8051	97036	26277	49393	98694
All	46403	30071	2162	7647	25046

Table 2 provides some more detailed statistics at three points in time, April 2000, April 2003 and April 2006[14]. We use the same presentation as Table 2 in Mitton and Vorkink (2007). At the end of each month, we divide investors into seven categories (first column of Table 2). The first five categories contain investors holding one to five stocks, the sixth category corresponds to investors holding six to nine stocks and the last category contains all diversified investors, considered to have positions in ten or more stocks. The second column shows the number of investors in each category. The four last columns provide summary statistics about portfolio values: the mean, the first quartile, the median and the third quartile. There is a large proportion (approximately 20%) of single-stock owners, and in all categories the mean portfolio value is much higher than the median portfolio value even among single-stock owners. In most cases, the mean is close to the third quartile.

The market activity of investors in our sample is also highly variable over time. Figure 3 shows the time- series of monthly trades. The bold (dashed) line represents buy (sell) trades. The large variations are essentially observed in the first three years, with a dramatic increase found in both kinds of trades up to April 2000. Approximately 110,000 monthly buy trades were executed per month in February, March and April 2000. An equivalent decrease is then observed until September 2001. Of course, even if the French market had remained open after 9/11, the volume was low that month and subsequent months. The remarkable fact is that sales were also at a very low level. It is not clear what *BSI* index means in this particular case. In the last five years of our sample period, the average level of trades is around 35,000 trades per month on each side.

14. The complete statistics for all months are available upon request.

Figure 3. Time-series of the number of monthly trades. The solid (dashed) line represents the evolution of purchases (sales)



2.2 Stock data

Stock prices come from two sources, Eurofidai[15] for stocks traded on Euronext and Bloomberg for the other stocks. We used daily prices for estimating the moments of the distribution of returns on stocks and investors' portfolios. In our sample, the universe of investments contains 2,491 stocks, meaning that each of these stocks has been traded at least once during the period under study. There are 1,191 French stocks with the remaining coming from all over the world but primarily from the U.S. (1,020 stocks), the United Kingdom (62), the Netherlands (34), Germany (31) and Italy (15). Despite the large number of U.S. stocks in our sample, the trades on French stocks account for over 90% of the trading volume, as shown in panel A of table 3. This table depicts the well-known home bias puzzle[16], which represents why most comparisons in this paper concern the French market. Moreover, a comparison between the number of U.S. stocks and the trading volume on these stocks reveals that these stocks are traded very unfrequently. Only 54,881 trades on U.S. stocks were executed, compared for example to the 366,138 trades made on the 34 Dutch stocks. Concerning holdings,

15. http://www.eurofidai.org. Part of this database has been recently used by Foucault *et al.* (2011) in their study of retail trading and volatility on the French market and by Baker *et al.* (2012) to study the contagion of sentiment across countries, including France and the U.S.

16. See Lewis (1999) and Karolyi and Stulz (2003) for a literature review on this topic.

Table 3. Trades and holdings for stocks of the 6 main countries where the firms are located. The first line of Panel A gives the number of stocks held at least one month by at least one investor in the sample.The second line indicates the number of trades for firms located in each of the six main countries in the sample. Panel B gives the percentage of investors holding stocks of the six countries under consideration at the end of each year of the period1999-2006.

Panel A: Trades in stocks of the 6 main countries							
	Total	France	Netherlands	U.S.A.	Great Britain	Germany	Italy
Nb stocks	2,491	1,191	34	1,020	62	31	15
Nb trades	8,258,809	7,510,017	366,138	54,881	27,207	22,849	5,059
Panel B: Percentage of investors holding stocks of the 6 main countries							
	Nb investors	France	Netherlands	U.S.A	Great Britain	Germany	Italy
1999	43.638	98.32	6.10	4.50	1.48	2.64	0,27
2000	58.699	96.93	23.37	3.90	3.04	2.05	0.23
2001	57.587	97.16	24.74	3.61	1.52	2.02	1.29
2002	53.040	97.06	21.33	3.85	1.64	1.85	0.61
003	56.952	96.97	21.05	3.97	1.61	1.19	0.70
004	52.050	97.17	20.21	3.89	1.72	1.17	0.41
2005	47.937	97.82	13.82	3.30	1.80	1.19	0.08
2006	42.100	98.13	14.69	2.75	2.18	0.98	0.14

panel B of table 3 reports at the end of each year from 1999 to 2006 the proportion of investors holding stocks of the 6 main countries in the database. For example, at the end of 2003, there were 56,952 investors holding stocks, of whom 96.97% held French stocks (meaning that approximately 3% held only foreign stocks), 21.05% held Dutch stocks and only 3.97% held U.S. stocks, despite the large number of U.S. stocks in the database (held at least once during the period).

3. Empirical study

3.1 Correlation analysis

In this section we compare the *MSI* index to three other indices, namely the French sentiment index (*FSI*), the index developed by Baker and Wurgler (2006), denoted by *BW*1, and the Buy-Sell imbalance index (*BSI*). We also analyze the correlation between these indices and the market index.

The correlations are reported in table 4. *MSI* and *BSI* are computed on a monthly basis using our sample of investors. MSI_t is obtained with a one-month transition matrix Q_t which is based on the sub-sample of investors present in the database at dates t and $t+1$. *BSI* for month t is calculated by cumulating daily trades over the month. However, for a trade on day s to be considered, the investor must still be in the database at the end of the day. As mentioned in our definition of *BSI*, trades of people leaving the database on a given day are not considered.

Table 4. Correlations between sentiment indices measured on a monthly basis over the period 1999-2006, namely the market sentiment index (*MSI*), the French sentiment index (*FSI*), the Baker-Wurgler index (*BW*1), and the Buy-Sell imbalance index (*BSI*). The two last columns give the correlations between sentiment indices and market return. Subscript *t* denotes contemporaneous returns and *t* +1 denotes lagged returns.

	FSI	BW1	BSI	RMRFt	RMRFt + 1
MSI	0.418***	0.143	0.717***	0.334***	0.213**
FSI		0.743***	0.382***	–0.047	–0.110
BW1			0.262**	–0.190*	–0.155
BSI				–0.057	–0.153
RMRFt					0.135

The indices are highly positively correlated, with the only exception being the correlation between *MSI* and the Baker-Wurgler; this correlation is not significant though it is positive (0.143). These positive correlations are not a surprise, even when comparing French and U.S. indices. This phenomenon was analyzed in Baker, Wurgler and Yuan (2012) who presented results of some contagion between sentiment indices in six countries, including France and the U.S. They found a .44 correlation between the global sentiment indices of the two countries. The fact that *MSI* is significantly correlated to the other indices is the first remarkable result with respect to the “poor” inputs used to calculate our index (at least according to the standards of classical finance theory). No information is used about which stocks are traded, and nothing is known about prices at which people trade or about traded volumes. Moreover, due to the convergence theorem of Markov chains, MSI_t does not depend on the diversification levels at date t because it is calculated with the variations of diversification between t and $t+1$.

The question is then whether there is a difference between *MSI* and the other usual indices. The answer appears in the two last columns of table 4. *MSI* is the only index with a positive and highly significant contemporaneous correlation with the market return (0.334). Even if we compare with *BSI* (calculated with the same raw data, that is trades of individual investors), we observe a large positive correlation between the two (0.717) but *BSI* is not correlated to the market return (–0.057).

Moreover, the correlation between *MSI* and the lagged market return remains significantly positive at the 5% level (0.213). The *BSI* index no longer has such a correlation. Nonetheless, the Baker-Wurgler index is negatively correlated with lagged market returns (–0.155).

To explore in depth these relationships, we enter a predictive regression approach in the next section. The purpose is to study the predictive power of the sentiment indices and perform systematic comparisons between the four indices of our study.

3.2 The predictive-regression approach

In this section, we compare the market sentiment index *MSI* to the others through predictive regressions on long-short portfolios based on size and on the book-to-market ratio. Baker and Wurgler (2007) introduce the “sentiment seesaw” to explain the effect of sentiment on stocks (figure 1, p133). They show that sentiment can have opposite effects on stock returns, depending on the difficulty of engaging in stock arbitrage. In high-sentiment periods, stocks that are “easy to arbitrage” may be undervalued and stocks that are difficult to arbitrage may be overvalued. The reverse appears in low-sentiment periods. If this theoretical prediction is true, a good sentiment measure should help to predict returns.

3.2.1. Portfolios based on size

We consider a long-short portfolio with a long position on small caps (more difficult to arbitrage) and a short position on large caps (easier to arbitrage)[17]. According to the "sentiment seesaw" approach, we expect the portfolio return to be high following low-sentiment periods and to be low following high-sentiment periods. In other words, when regressing the return of the long-short portfolio, we expect a negative sign for the coefficient of the lagged sentiment measure.

Our methodology contains two steps. The first one estimates the following equation:

$$R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s.Sentiment_{t-1} + \varepsilon_t \qquad (14)$$

where $Sentiment_t$ is the sentiment index for month t and may be *FSI*, *BW1*, *MSI*, *BSI*.

In the second step, we control for Fama-French-Carhart-LOT factors. The regression model is then the following:

$$R_{Smallcaps,t} - R_{Bigcaps,t} = c + \beta_s.Sentiment_{t-1} + \beta_X X_{t-1} + \varepsilon_t \qquad (15)$$

The vector **X** of control variables includes the market factor, the three Fama-French-Carhart factors, and the LOT illiquidity factor. The four first control variables are obtained directly from the Eurofidai database and the illiquidity factor in a given month is calculated as the percentage of daily zero returns over the set of stocks traded at least once during this month.

Unfortunately, the two above regressions produce biased estimators of β_s when *Sentiment* is an autoregressive process. Such a bias occurs because the residuals of the regression of $Sentiment_t$ on $Sentiment_{t-1}$ may be correlated with the residuals ε_t of regressions (14) and (15). In that case, the predictive power of *Sentiment* could be overstated. To deal with the estimation problems, Stambaugh (1999) and Amihud and Hurvich (2004) propose a simple way to reduce the bias of the estimator.

The regression of $Sentiment_t$ on $Sentiment_{t-1}$ is written

$$Sentiment_t = \theta + \rho Sentiment_{t-1} + \nu_t \qquad (16)$$

17. These portfolios are directly provided by Eurofidai.

Table 5. Coefficients of sentiment when regressing the returns of a long-short portfolio based on size, on sentiment measures (with the reducing-bias technique of Amihud-Hurvich, 2004). Panel A gives the coefficient of sentiment in the simple regression: $R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \phi v_t + \varepsilon_t$ Panel B provides the same coefficient when controlling for Fama-French factors, Carhart momentum factor and LOT liquidity factor. The regression equation is: $R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{x}} \mathbf{X}_{t-1} + \phi v_t + \varepsilon_t$ where the matrix **X** includes the market factor and the four Fama-French-Carhart-LOT factors. The sentiment measures are the market sentiment index *MSI*, the French sentiment index (*FSI*), the Baker-Wurgler index (*BW*1), and the buy-sell imbalance index (*BSI*). When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.113.

	MSI	*FSI*	*BW1*	*BSI*
Panel A: Equation 13 without controls				
b	–0.051**	–0.001*	–0.004	–0.105*
t-stat	–2.575	–1.829	–0.810	–1.710
p-val	0.012	0.071	0.420	0.090
$\overline{R}^2$	0.048	0.031	0.012	0.015
Panel A: Equation 14 with controls				
d	–0.075***	–0.000	0.001	–0.092
t-stat	–3.586	–0.830	0.280	–1.412
p-val	0.000	0.408	0.779	0.161
$\overline{R}^2$	0.215	0.105	0.108	0.115

1) These authors estimate ρ in regression (16) and correct the estimate $\hat{\rho}$ as follows

$$\hat{\rho}^c = \hat{\rho} + \frac{1 + 3\hat{\rho}}{n} + \frac{3(1 + \hat{\rho})}{n^2} \qquad (17)$$

where $n = 95$ in our case.

2) The residuals of regression (16) are estimated using $\hat{\rho}^c$ and denoted by $v^c = (v_t^c,\ t = 1, \ldots n)$. The vector v^c is then introduced in regression (14) which becomes

$$R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \phi v_t^c + \beta_s Sentiment_{t-1} + \varepsilon_t \quad (18)$$

Finally, the corrected standard error of β_s is obtained as follows

$$\widehat{SE}^c(\beta_s) = \sqrt{\hat{\phi}^2 Var\left(\hat{\rho}^c\right) + \widehat{SE}^2(\beta_S)} \quad (19)$$

$\widehat{SE}^c(\beta_s)$ is used to calculate the significance of the estimator of β_s in table 5 (the same approach will also be used in tables 6 and 8).

The results appear in table 5. Panel A (B) provides the regression coefficients of the sentiment measures for equation 14 (15) without (with) control for the Fama-French-Carhart-LOT factors. In all cases but one, we obtain the expected negative sign for the regression coefficient. This finding indicates that, on average, a period of high sentiment is followed by a low return on the long-short portfolio, even after controlling for the market, size, book-to-market, momentum and illiquidity factors. In the two versions of the analysis, *MSI* is significant and delivers the highest $\overline{R}^2$.

Our results show that portfolio diversification dynamics of individual investors carry valuable information to predict returns, but not all trades are informationally equivalent. The results obtained for the *BSI* indicator show that many trades are not informative about sentiment and future returns. It is in fact not surprising because trades realized by investors holding large and diversified portfolios can be motivated by portfolio management concerns, not by sentiment. These trades enter for a large part in the *BSI* index but say nothing about optimism/pessimism of investors.

3.2.2. Portfolios based on the book-to-market ratio

Following exactly the methodology of the preceding subsection, we build a long-short portfolio with a long position on a portfolio of growth stocks and a short position on a portfolio of value stocks. The dependent variable is now $R_{Growth,t} - R_{Value,t}$ and the independent variables are the same as in equations (15) and (14). As before, we expect a negative sign for the coefficient of the sentiment measure.

The results are reported in table 6.

Table 6. Coefficients of sentiment when regressing the returns of a long-short portfolio based on book-to-market ratio, on sentiment measures (with the reducing-bias technique of Amihud-Hurvich, 2004). Panel A gives the coefficient of sentiment in the simple regression:
$R_{Growth,t} - R_{Value,t} = \alpha + \beta_s Sentiment_{t-1} + \phi v_t + \varepsilon_t$ Panel B provides the same coefficient when controlling for Fama-French factors, Carhart momentum factor and LOT liquidity factor. The regression equation is:
$R_{Growth,t} - R_{Value,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_x \mathbf{X}_{t-1} + \phi v_t + \varepsilon_t$ where the matrix **X** includes the market factor and the four Fama-French-Carhart-LOT factors. The sentiment measures are the market sentiment index *MSI*, the French sentiment index (*FSI*), the Baker-Wurgler index (*BW*1), and the buy-sell imbalance index (*BSI*). When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.114.

	MSI	*FSI*	*BW1*	*BSI*
Panel A: Equation 13 without controls				
b	–0.038**	–0.001**	–0.008	–0.070
t-stat	–2.283	–2.236	–1.62	–1.340
p-val	0.025	0.028	0.107	0.183
$\bar{R}^2$	0.054	0.062	0.000	0.000
Panel B: Equation 14 with controls				
d	–0.023	–0.001	–0.004	–0.009
t-stat	–1.188	–1.603	–0.910	–0.155
p-val	0.238	0.112	0.365	0.877
$\bar{R}^2$	0.126	0.128	0.120	0.095

In the uncontrolled regression, only *FSI* and *MSI* are significant at the 5% level with the expected sign. The two other indices are not significant, especially *BSI*, though this measure is based on more information than *MSI*. No index is significant in the controlled regression.

We now need to test the economic relevance of our index. In other words, how does a sentiment-based strategy perform when compared to uninformed or buy-and-hold strategies?

3.3 Economic relevance of the market sentiment index

The first argument showing the economic significance of the *MSI* is the fact that an increase of one-standard deviation of the index (equal to 0.21) decreases the next-month return of the long-short size-based portfolio by 1.05%, (using the regression coefficient in table 5 for the uncontrolled case). The second argument of economic relevance is the performance provided by a strategy based on *MSI*. In table 4 we showed that *MSI* is significantly correlated to the market index return, and that the correlation is still 0.213 with the next-month return. The question is to know whether this information gives rise to profitable strategies.

In this section, our methodology is inspired by Brown and Cliff (2004). The intuition that drives the method is the following; if the sentiment index is a good predictor of future returns, we should invest large (small) amounts in the market index when the preceding month sentiment index is high (low).

We test such a strategy and compare its performance to the performance of a buy-and-hold index portfolio and to that of randomly generated (thus uninformed) dynamic strategies.

We assume that investors invest a part of their wealth in the market portfolio and the remaining part in the risk-free rate. The initial wealth W_0. is equal to 1 for each strategy. The wealth process of the sentiment strategy is denoted by *W*. It is defined as follows

$$W_0 = 1 \qquad (20)$$
$$W_t = W_{t-1} \times [MSI_{t-1}(1 + RM_t) + (1 - MSI_{t-1})(1 + rf_t)]$$

where rf_t is the risk-free rate on month *t* and RM_t is the return on the index portfolio[18]. It is important to note that the stochastic process of quantities is predictable and then consistent with an implementation in real conditions.

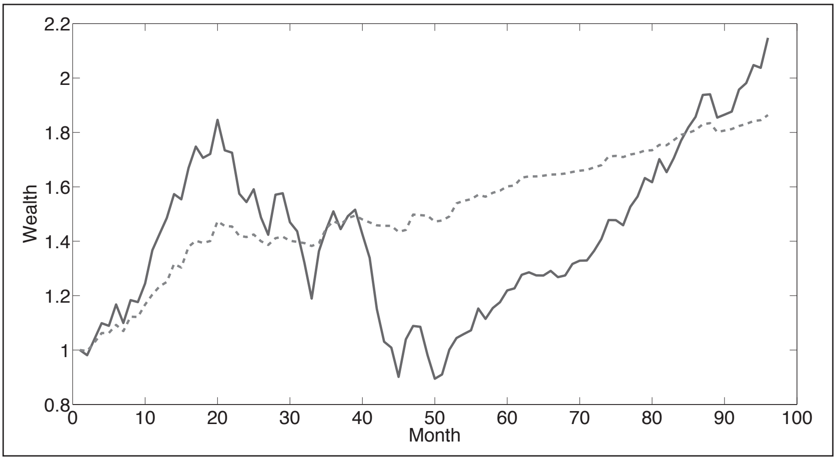
At the end of month $t - 1$, the sentiment index is calculated and a proportion MSI_{t-1} is invested in the market index at the beginning of month *t*. This investment pays off $W_{t-1} \times MSI_{t-1}(1 + RM_t)$ at the end of month *t* for the risky part of the portfolio.

18. Eurofidai provides an equally and a value-weighted index. The latter is used in our study.

The remaining amount, equal to W_{t-1} $(1 - MSI_{t-1})$ is invested in the risk-free asset. We therefore obtain a sequence of returns on the strategy, denoted by *RS*, and we compare the performance of *RS* to the buy-and-hold strategy invested in the index portfolio.

$$RS_t = MSI_{t-1} RM_t + (1 - MSI_{t-1})\ rf_t) \qquad (21)$$

Figure 4. The solid curve represents the evolution of the value of one monetary unit invested in the index. The dashed curve represents the evolution of the value of one monetary unit invested in the sentiment-driven strategy, that is the process *W* defined in equation 20



[Picture: *Wealth.eps*, click on me and press F9]

The wealth process *W* is represented on figure 4. The bold line gives the evolution of the buy-and-hold strategy and the dashed line is the process *W* described in equation (20) It appears that the volatility of the sentiment strategy is much smaller than the volatility of the index. In fact, the monthly Sharpe ratio of the index is 0.13 and the corresponding ratio for the sentiment strategy described in equation (20) is 0.263 (with a risk-free rate equal to the 3-month Euribor rate).

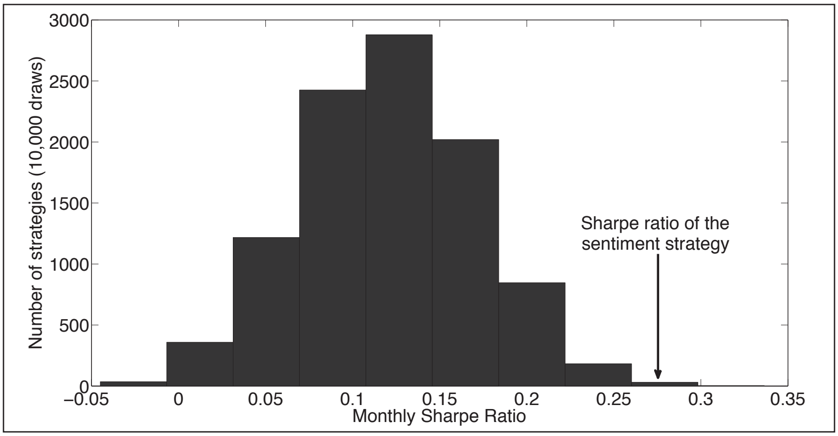
This comparison between the sentiment strategy and the index is not sufficient to conclude that *MSI* produces valuable indications for the investment process. Our findings may be due to luck.

To determine whether this is the case, we simulate uninformed dynamic strategies. In equation (20), *MSI* take 95 successive values, one per month.

MSI is the percentage invested in the risky asset (the index). What we call an uninformed strategy is a stochastic process of wealth where the 95 successive proportions invested in the index are random numbers drawn between 0 and 1. We draw 10,000 such random sequences, and use each sequence in equation (20) in place of *MSI*.

We calculate the Sharpe ratios of the 10,000 uninformed strategies and build the histogram (Figure 5) of the distribution of uninformed Sharpe ratios.

Figure 5. Histogram of the Sharpe ratio of the uninformed dynamic strategy



Among the 10,000 Sharpe ratios, 99.6% are below the monthly Sharpe ratio of the sentiment driven strategy. Consequently, we can reject the null hypothesis of luck with a reasonable degree of confidence.

4. Robustness checks

In this section, we perform several robustness checks in relation with the assumptions of our analysis. First, we analyze the sensitivity of the sentiment index *MSI* to the choices made to calculate this sentiment index. Up to now, *MSI* was obtained by assuming a Markov chain with 20 states, and no constraint was imposed on the portfolio value of investors. We kept in the database all investors with portfolios worth more than 100. In this section we test the robustness of our results to variations of these two variables.

We build 3×3 time-series of indices by considering three possible values for K(K = 10, 20 or 30) and three possible values for the minimum portfolio value W_{min} (W_{min} = 100; 1,000; 5,000). The second test concerns the horizon of prediction. We perform the same analyses as before, except that 3-month and 6-month returns on long-short portfolios based on size are used in place of monthly returns.

4.1 The number of states and the minimum wealth

We refer to Liu (2013) to explain why the sensitivity analysis with respect to W_{min} is important. Liu (2013) develops a model showing that the underdiversification of individual portfolios may come from low wealth levels and solvency constraints. In short, "poor" investors, subject to solvency constraints, must invest much of their wealth in the risk-free asset. Consequently, for the remaining part, they focus only on expected returns, and not on the variance of returns. The optimal risk-return tradeoff for them is to invest the remainder of their wealth in high expected-return stocks, that are also high-risk stocks.

The intuitive justification of Liu's model is the following. An investor with only a few hundred euros to invest in the stock market will buy a single stock. When her wealth increases, a second stock is introduced in the portfolio because the marginal benefit of underdiversification is compensated by the supplement of risk generated by the single-stock portfolio. This reasoning has nothing to do with sentiment but relies on simple, and perhaps convincing arguments. Consequently, to determine whether our sentiment measure in fact measures sentiment (and not solvency constraints), we restrict the database to investors whose portfolio value is at least 1,000 € and 5,000 €.

Table 7 shows the correlations between the 9 versions of the sentiment index. The first line and the first column specify the index under consideration. For example, 20/1000 means that *MSI* is calculated with K = 20, and with the subsample of investors holding portfolios worth more than 1,000 €.

Table 7. Correlations between versions of *MSI*. The first column and line provide the parameters used to calculate the correlation. The first number is the number of states of the Markov chain and the second number is the minimum wealth below which investors are neglected in the calculation of the sentiment index.

	10/1000	**10/5000**	**20/100**	**20/1000**	**20/5000**	**30/100**	**30/1000**	**30/5000**
10/100	0.985	0.897	0.969	0.970	0.946	0.930	0.935	0.929
10/1000		0.957	0.942	0.963	0.970	0.897	0.917	0.936
10/5000			0.838	0.884	0.945	0.788	0.827	0.885
20/100				0.993	0.949	0.990	0.990	0.969
20/1000					0.978	0.978	0.989	0.986
20/5000						0.924	0.952	0.985
30/100							0.996	0.965
30/1000								0.985

All correlations are close to 1, except for the index 10/5000. The correlations of this index with the indices calculated with more than 10 stocks are lower. The explanation of this special case is simple. Increasing the minimum portfolio value has essentially two effects. First, it decreases the number of investors included in the analysis and, second, it increases the mean number of stocks in portfolios. For example, when the minimum portfolio value is 1,000 € (5,000 €) the average number of investors included in the calculation becomes 42,355 (27,878), down from 51,340 without constraints[19]. Moreover, the results for single-stock owners show that there are an average of 11,192 in the complete sample but only 5,092 (1,343) when the minimum portfolio value is 1,000 (5,000 €).

19. These figures remain sufficient to evaluate transition matrices with good accuracy but change the long-run equilibrium distribution of the Markov chain of diversification levels. Consequently, they also change the sentiment measure *MSI*.

Table 8. Coefficients of *MSI* when regressing the returns of a long-short portfolio based on size, on sentiment (with the reducing-bias technique of Amihud-Hurvich, 2004). The first column gives the combination K/W_{min} where K in the number of states of the Markov chain and W_{min} the minimum portfolio value of the investors entering the analysis.
Panel A gives the coefficient of *MSI* in the simple regression:
$R_{Smallcaps,t} - R_{Bigcaps,t} = a + bMSI_{t-1} + \phi v_t + \varepsilon_t$ Panel B provides the same coefficient when controlling for Fama-French factors, Carhart momentum factor and LOT liquidity factor. The regression equation is:
$R_{Smallcaps,t} - R_{Bigcaps,t} = C + dMSI_{t-1} + \beta_{\mathbf{x}}\mathbf{X}_{t-1} + \phi v_t + \varepsilon_t$ where the matrix **X** includes the market factor and the three Fama-French factors . (*BSI*). When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.113.

	d	t-stat	p-val	$\overline{R}^2$
Panel A: Equation 13 without controls				
10/100	–0.044**	–2.237	0.028	0.042
10/1000	–0.046**	–2.049	0.043	0.034
10/5000	–0.047	–1.617	0.109	0.018
20/100	–0.051**	–2.575	0.012	0.058
20/1000	–0.052**	–2.532	0.013	0.056
20/5000	–0.054**	–2.431	0.017	0.052
30/100	–0.056***	–2.706	0.008	0.064
30/1000	–0.057***	–2.676	0.009	0.063
30/5000	–0.058***	–2.679	0.009	0.064
Panel B: Equation 14 with controls				
10/100	–0.073***	–3.376	0.001	0.201
10/1000	–0.073***	–3.044	0.003	0.183
10/5000	–0.065**	–2.183	0.032	0.142
20/100	–0.075***	–3.56	0.000	0.215
20/1000	–0.076***	–3.520	0.000	0.211
20/5000	–0.074***	–3.236	0.002	0.194
30/100	–0.079***	–3.583	0.000	0.218
30/1000	–0.079***	–3.565	0.000	0.216
30/5000	–0.078***	–3.467	0.000	0.209

The average numbers of stocks in portfolios are equal to 5.92, 6.8 and 8.92, for the minimum portfolio values of 100 €, 1,000 € and 5,000 €, respectively[20]. It turns out that the index 10/5000 is not very volatile because the proportion of investors staying in the same category (holding more than 10 stocks) in two consecutive months is large. In fact, the standard deviation of the 10/5000 index is 0.14 and the standard deviation of the base case scenario (20/100) is 0.21. This difference is simply due to the high-average number of stocks in portfolios worth more than 5,000 €.

We then perform the regressions of equations (14) and (15) with the 3×3 sentiment measures. The results appear in table 8. The coefficients of *MSI* slightly change when the number of states of the Markov chain increases or when W_{min} varies. However, the changes are not important, either on the significance of the coefficient or on the adjusted R^2 of the regression.

As a conclusion, we can say that *MSI* is quite robust to changes in parameters like K or W_{min} when it comes to predict future returns of long-short portfolios based on size. Similar (unreported) results are obtained with portfolios based on the book-to-market ratio.

4.2 The horizon of prediction

Tables 9 and 10 provide the regression results when 3-month returns and 6-month returns are used instead of monthly returns. The results are provided for the twelve possible combinations of sentiment measures. The first nine rows in each table concern the *MSI* measure, with various minimum levels of wealth and different number of states of the Markov chain (as in table 8). The bottom three lines contain the coefficients of the other sentiment measures, *FSI*, *BW*1 and *BSI*.

20. This finding gives some credit to the model of Liu (2013) and reinforces the necessity of the sensitivity analysis.

Table 9. Coefficients of sentiment when regressing the quarterly returns of a long-short portfolio based on size, on sentiment measures (with the reducing-bias technique of Amihud-Hurvich, 2004). Panel A gives the coefficient of sentiment in the simple regression: $R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \phi v_t + \varepsilon_t$ where $R_{Smallcaps,t}$ is the quarterly return of the small caps portfolio and $R_{Bigcaps,t}$ the quarterly return of the big caps portfolio, the quarter under consideration starting on month t and ending on month $t+2$. Panel B provides the same coefficient when controlling for Fama-French factors, Carhart momentum factor and LOT liquidity factor. The regression equation is: $R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{x}} \mathbf{X}_{t-1} + \phi v_t + \varepsilon_t$ where the matrix **X** includes the market factor and the four Fama-French-Carhart-LOT factors. The sentiment measures are the market sentiment index *MSI*, the French sentiment index (*FSI*), the Baker-Wurgler index (*BW*1), and the buy-sell imbalance index (*BSI*). When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.057.

	d	t-stat	p-val	$\overline{R}^2$
Panel A: Equation 13 without controls				
10/100	–0.092**	–2.349	0.021	0.051
10/1000	–0.093**	–2.085	0.040	0.034
10/5000	–0.100*	–1.729	0.087	0.014
20/100	–0.113***	–2.882	0.005	0.082
20/1000	–0.112***	–2.725	0.008	0.070
20/5000	–0.112**	–2.542	0.013	0.056
30/100	–0.131***	–3.163	0.002	0.099
30/1000	–0.127***	–3.006	0.003	0.088
30/5000	–0.124***	–2.870	0.005	0.077
FSI	–0.002**	–2.597	0.011	0.053
BW1	–0.019*	–1.755	0.083	0.015
BSI	–0.297**	–2.434	0.017	0.049
Panel B: Equation 14 with controls				
10/100	–0.143***	–3.134	0.002	0.141
10/1000	–0.138***	–2.737	0.007	0.118
10/5000	–0.127**	–2.041	0.044	0.084
20/100	–0.158***	–3.573	0.001	0.169

	d	t-stat	p-val	$\overline{R}^2$
20/1000	–0.153***	–3.361	0.001	0.156
20/5000	–0.144***	–2.983	0.004	0.135
30/100	–0.172***	–3.768	0.000	0.182
30/1000	–0.166***	–3.584	0.001	0.171
30/5000	–0.157***	–3.315	0.001	0.156
FSI	–0.002*	–1.727	0.087	0.071
BW1	–0.012	–1.011	0.315	0.050
BSI	–0.288**	–2.118	0.037	0.091

As expected, the significance of *MSI* slightly deteriorates on longer prediction horizons; however, *MSI* remains largely significant and outperforms the other measures when the most detailed information is considered, that is 30 states for the Markov chain and 100 for the minimum wealth (then including all the investors, even the less wealthy). Nevertheless, there is one exception in table 10 where the French sentiment index becomes significant at the 1% level in the prediction of 6-month returns; it is in fact slightly more significant (in terms of *t*-stat) than the *MSI*. This result may be explained by the fact that *FSI* is based on the answers of consumers to questions about their economic and financial future. It is reasonable to argue that people do not think to their immediate future when they answer these questions. On the opposite, the value of the *MSI* in a given month is deduced from some trades realized during that month, trades that can be easily reversed next month.There is then no reason to extract long-term information from this index because investors can change quickly their portfolio, and their short-term predictions about the market evolution. Nothing in our index implies a long-term commitment, even if statistical results show some persistence in the performance of the *MSI* index on different horizons.

Table 10. Coefficients of sentiment when regressing the 6-month returns of a long-short portfolio based on size, on sentiment measures (with the reducing-bias technique of Amihud-Hurvich, 2004). Panel A gives the coefficient of sentiment in the simple regression:
$R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \phi v_t + \varepsilon_t$ where $R_{Smallcaps,t}$ where is the 6-months return of the small caps portfolio and the 6-months return of the big caps portfolio, the semester under consideration starting on month t and ending on month $t + 5$. Panel B provides the same coefficient when controlling for Fama-French factors, Carhart momentum factor and LOT liquidity factor. The regression equation is:
$R_{Smallcaps,t} - R_{Bigcaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{x}} \mathbf{X}_{t-1} + \phi v_t + \varepsilon_t$ where the matrix **X** includes the market factor and the four Fama-French-Carhart-LOT factors . The sentiment measures are the market sentiment index *MSI*, the French sentiment index (*FSI*), the Baker-Wurgler index (*BW*1), and the buy-sell imbalance index (*BSI*). When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.1368.

	d	t-stat	p-val	$\overline{R}^2$
Panel A: Equation 13 without controls				
10/100	–0.095**	–2.370	0.020	0.054
10/1000	–0.096**	–2.113	0.037	0.037
10/5000	–0.105*	–1.764	0.081	0.016
20/100	–0.116***	–2.902	0.005	0.087
20/1000	–0.116***	–2.753	0.007	0.076
20/5000	–0.117**	–2.583	0.011	0.061
30/100	–0.134***	–3.177	0.002	0.104
30/1000	–0.131***	–3.027	0.003	0.094
30/5000	–0.129***	–2.905	0.005	0.083
FSI	–0.002**	–2.646	0.010	0.057
BW1	–0.02*	–1.753	0.083	0.015
BSI	–0.301**	–2.424	0.017	0.051
Panel B: Equation 14 with controls				
10/100	–0.148**	–2.331	0.022	0.186
10/1000	–0.127*	–1.800	0.075	0.161
10/5000	–0.102	–1.173	0.244	0.138
20/100	–0.170***	–2.761	0.007	0.216

	d	t-stat	p-val	$\overline{R}^2$
20/1000	–0.156**	–2.438	0.017	0.198
20/5000	–0.139**	–2.057	0.043	0.181
30/100	–0.189***	–2.968	0.004	0.226
30/1000	–0.176***	–2.716	0.008	0.212
30/5000	–0.164**	–2.478	0.015	0.202
FSI	–0.004***	–3.311	0.001	0.223
BW1	–0.034**	–2.269	0.026	0.173
BSI	–0.317*	–1.709	0.091	0.177

5. Concluding remarks

This paper proposes an original measure of market sentiment based only on changes in diversification choices by retail investors. The purpose of this paper is to extract information about market sentiment (optimism/pessimism) and to show that this sentiment measure enters significantly in the short-term prediction of market returns. We show that this new measure outperforms several other indices (based on surveys, buy-sell imbalances, or macroeconomic variables) in this task. Our contributions are theoretical and empirical. To the best of our knowledge, the sentiment index we introduce in this paper is completely new and we show that the use of Markov chains facilitates the extraction of information from the data. On the empirical side, our index can be easily implemented by banks on their client accounts. Our measure enables users to follow the market sentiment dynamically and to update it frequently.

Finally, the empirical study proposed in this paper concerns a large sample of French individual investors. To confirm the usefulness of our index, it would be useful to duplicate and enrich our test on other samples of investors, especially those in other countries.

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Appendix

Appendix 1: proof of proposition 3

Proof. We denote P_0 the initial distribution of portfolios; $P_0 = (p_k^0, k = 1,....,K)$ meaning that $P(N_0 = k) = p_k^0$ .The distributions of P_1 and P_1^* depending on the transition matrix are

$$P_1 = P_0 Q \text{ and } P_1^* = P_0 Q^* \qquad (22)$$

We then have

$$E(N_1) = \sum_{k=1}^{K} kP_1(k) = \sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)Q(j,k) \qquad (23)$$

$$= \sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)\left(Q^*(j,k) + \Delta_{jk}\right) \qquad (24)$$

$$= \sum_{k=1}^{K} kP_1^*(j) + \sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)\Delta_{jk} \qquad (25)$$

$$= E(N_1^*) + \sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)\Delta_{jk} \qquad (26)$$

It remains to transform the last term $\sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)\Delta_{jk}$ by changing the order of summation.

$$\sum_{k=1}^{K} k \sum_{j=1}^{K} P_0(j)\Delta_{jk} = \sum_{j=1}^{K} P_0(j) \sum_{k=1}^{K} k\Delta_{jk} \qquad (27)$$

But the characteristics of Δ defined above imply $\sum_{k=1}^{K} k\Delta_{jk} \geqslant 0$ for any j implying $E(N_1) \geqslant E(N_1^*)$.

The same reasoning can be applied at any date and leads to $E(N_t) \geqslant E(N_t^*)$ for any t, and finally to $E(N_{\infty,t}) \geqslant E(N_{\infty,t}^*)$.

Appendix 2: Sentiment indices

We briefly present the French sentiment index and the two Baker-Wurgler indices and give references for more detailed presentations.

A. The French consumer sentiment index

It is based on the same principles as the ICS. The French Institute of statistics realizes a monthly phone survey[21] with around 2,000 households. It also provides information along several dimensions linked to perception of economic conditions and expectations. The results are presented as differences between good and bad opinions for each dimension. The synthetic index used in this paper is based on the following indicators[22]:

1) Past personal financial situation
2) Expectation about future evolution of financial situation
3) Opportunity to invest in consumption goods
4) Past standard of living
5) Expectation about future evolution of standard of living
6) Unemployment perspectives
7) Saving capacity

The synthetic measure is obtained through a factor analysis. There also exists a summary index which is like the ICS, an arithmetic average of the items 1 to 5.

B. The Baker-Wurgler indices

Baker and Wurgler (2006) argue that it is difficult to rely on a unique variable to represent sentiment. They build two sentiment indices as linear combinations of the six following variables:

1) The closed-end fund discount
2) The natural logarithm of the NYSE share turnover ratio (detrended by the 5-year moving average)
3) The number of IPOs
4) The average first-day return on IPOs
5) The share of equity issues in total equity and debt issues
6) The dividend premium (log difference of the average market-to-book ratios of dividend payers and non payers)

The authors define their first index as the loadings on the first principal component in a PCA of the 6 variables. One possible criticism of this index (mentioned by Baker and Wurgler) is that it is difficult to disentangle what

21. The methodological details are explained at http://www.insee.fr/fr/indicateurs/ind20/method_idconj_20.pdf

22. The complete questionnaire can be found at http://www.bdm.insee.fr/bdm2/documentationGroupe.action?codeGroupe=389

comes from sentiment and what is driven by the business cycle in the loadings. Consequently, they build a second index with the same approach, except that the six variables are now the residuals of the regression of the initial variables on growth in the industrial index, growth in consumer durables, non durables and services and a dummy variable for NBER recessions (see Baker and Wurgler, 2006, p 1657).