USING THE DYNAMIC FACTOR MODEL TO IDENTIFY INDIVIDUAL INVESTORS BIAS IN CANADIAN EQUITY MARKET DATA

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1. INTRODUCTION

The financial crisis of 2008 had adverse effects on economies all over the world, some of which could be still felt to the present day, but the crisis did more then just impact macroeconomic performance, it also had an effect on shaping economic and financial theory.

The Great Recession can be characterized as the market failing to adhere to the Efficient Market Hypothesis that held true for a great part of the twentieth century. One view is that the Great Recession, as a failure of an efficient market, could be in part attributed to heuristic behavior of individual investors, or their following a rule-of-thumb.

The Efficient Market Hypothesis or EMH was described by Eugene Fama (1970) as the efficiency of stock market in providing players with all the information necessary to make rational purchase-selling decisions. The stock market efficiency was considered to be equally perfect when it came to "individual stocks and … (to) stock market as a whole" (Malkiel, 2003). This market efficiency is fuelled by the assumption that whenever new information appeared, it would be available to all interested parties fully and at the same time, thus stock prices would reflect such information in real time. Thus in combination with the assumption of fully rational, utility maximizing agents, the market prices were thought to reflect the true fundamental value of equity. But how realistic are the assumptions of EMH, is it possible that agents are not fully rational but are influenced by emotional states, which cause them to make biased decisions, and therefore affect equity prices and market efficiency? The purpose of this study is to test empirically, using Canadian data, for the presence of evidence of loss aversion heuristic in individuals' investment decisions, reflected through countercyclical changes in equity risk premiums. The contribution of this study is in two areas; first it contributes to the existing literature on market efficiency, validity of the EMH and one of its main assumptions namely, fully rational agents, and second, this study helps further the understanding of Canadian investors dispositions to bias or heuristics, while shedding light on possible structure of their risk preferences.

The Efficient Market Hypothesis does not take into account the psychology of individual investors and how it influences asset prices, risk premiums and market efficiency as a whole. In other words, the Efficient Market Hypothesis does not account for the fact that agents can be 'irrational' and as a result, markets can be inefficient. To incorporate such possibilities, Behavioral Economics and Behavioral finance have emerged as new fields of study. Behavioral finance is defined as "the study of the influence of psychology on the behavior of financial practitioners and the subsequent effect on markets" (Sewell, 2007). Behavioral finance is primarily concerned with limits to rationality of market participants, which is explained in terms of heuristics. Heuristics are defined as trial-and-error behavior of individual investors (Singh, 2002). The main idea is that individual investors market decisions may be irrational, in the sense that they are based on a rule of thumb, or heuristic, rather than a deliberate rational choice.

Loss aversion is one of the many types of heuristics or biases, which refers to individual investors' perceptions of losses and gains in the market. Two scholars, Kahneman and Tversky, first introduced loss aversion in 1979. They defined loss aversion as: "an individual is loss averse if she or he dislikes symmetric 50-50 bets and, moreover, the aversiveness to such bets increases with the absolute size of the stakes" (Kahnemann & Tversky, 1979). In other words, loss averse investors are more sensitive to losses than to gains, of the same amount of money (Rauf, 2014). Loss aversion is a bias that has effect on individuals' sensitivity to changes in personal wealth. It manifests itself through the difference in the absolute magnitude of the effect of the change in wealth on persons risk tolerance in choice under uncertainty, and can be viewed as an aspect of loss/gain comparison independent of ranking of outcomes and their likelihood of occurrence (Schmidt and Zank 2005). Hence the limit of rationality, loss averse individuals care more about not loosing money, ignoring the subjective probability of such outcomes. This leads investors to becoming trying to avoid losses at all costs. Investors may hold on to an underperforming stock expecting it to improve over time, such behavior may lead to significant losses in the long-run. On the other hand, myopic loss aversion, which refers to a case when an investor makes an irrational short-term decision to prevent immediate losses, hurts a promising stock with long-term positive prospects.

This study is focused on loss aversion specifically, for two reasons; first loss aversion is widely used in economic literature to explain a number of phenomenon, important examples of which are the equity premium puzzle (Mehra and Prescott 1985; Benartzi and Thaler 1995), endowment effect (Thaler 1980), asymmetric price elasticities (Hardie et al. 1993), and downward- sloping labour supply (Dunn 1996; Camerer et al. 1997; Goette et al. 2004) (Abdellaoui, Bleichrodt, and Paraschiv 2007). Thus it is interesting to investigate whether the heuristic that is used to explain economic anomalies may be identified in the data, and hence shine light on the validly of explanations of such anomalies. And second, loss aversion is documented to have different magnitudal effect between losses and gains, the empirical estimates are in the neighborhood of 2, meaning the disutility of loosing something is twice as great as the utility of acquiring it (Tversky and kahneman 1992, Kahneman, Kritsch and Thaler 1990) (Benartzi and Thaler 1993). This difference in the magnitude of the effect, as well as its direction, is the identifying characteristic of this bias and key part of the analysis. Since loss aversion is a concept about individuals' preferences, which are not measured directly, we will need to induce from market data the effect of changes in wealth on investors risk preferences. Since this is not feasible on an individual level, we approach the issue on an aggregate level, meaning risk premiums are assumed to reflect the average investors perception of risk in the market. Business cycle fluctuations will be used to signal periods of wealth gains and losses.

A brief review of academic literature on the effect of loss aversion on equity prices, returns, and market efficiency as a whole is provided next.

1.1 HOW LOSS AVERSION AFFECTS THE FUNDAMENTAL VALUE OF ASSET AND MARKET EFFICIENCY

According to Easley and Yang (2011), loss aversion may or may not influence the fundamental value of asset prices. Whether it influences the prices or not depends on whether loss averse investors stay in the market for a long term or get expulsed from the market by their more aggressive counterparts. All other things equal, in a market where all investors are heterogeneous and all assets in the market are dynamic, "loss averse investors will be driven out of the market and thus they do not affect prices in the long run" (Easley & Yang, 2011).

Other scholars, Ng and Sadeghi (2005), state that there is little difference between price fluctuation caused by loss averse and otherwise rational investors. The authors further state that such differences, if any, stem from cultural attitudes, the level of economic development of a country as well as financial markets development in a given country.

A notion of myopic loss aversion is widely discussed in scientific literature. Scholars, Mayhew and Vitalis (2014), state that while myopic loss aversion is a characteristic mostly exhibited by less experienced individual investors, at times, more experienced individual investors exhibit it as well. In their empirical study, they demonstrate that if the overall market manages to mitigate the effects of myopic loss aversion, then the overall market is not influenced by its effects (Mayhew & Vitalis, 2014).

Grune and Semmler (2007) state that individual investors, who act under loss aversion heuristic and who have experienced losses in the past, become more loss averse when facing a price decrease for their assets. In production economies, a characteristic of fast-growing economies, such behaviour leads to a generalized price reduction in the market. The authors further state that in such conditions loss averse individual investors do not need to suffer significant losses to lead them to make changes in their portfolio (Grunne & Semmler, 2007).

Andries (2011) states that even small changes in loss aversion lead to a significant fluctuation in asset prices. The author further states that the greater the risk exposure is, the greater the variation in price.

Breaban and Noussair (2004) state that the fundamental value of asset prices stays unchanged for while prior to the beginning of a trend. As per their experiment, loss averse investors tend to demonstrate "close adherence to fundamental values when the trajectory follows a decreasing, than when it has an increasing trend". They conclude that higher loss aversion drives the quantity of stocks traded down. According to the authors, "the variation between groups in … loss aversion … explains an additional 44% … compared to a model including only treatment, experience level, and subject pool" (Breaban & Noussair, 2014).

Barberis and Huang (2001) demonstrate that in a market with loss averse individuals "individual stock returns have higher means, and are more volatile then the underlying cash flows." On a broader sense, when considering individual valuation of portfolios, the authors state that loss aversion changes the behavior of stock return considerably.

Lastly, Amonlirdviman and Carvalho (2010) state that loss aversion can be used to explain why high equity premiums might be consistent with plausible levels of risk aversion. The main idea is that "different utility impact of wealth gains and losses leads loss-averse investors to behave similarly to investors with high risk version." In extreme cases, loss averse investors may reduce their demand for risky assets and switch to holding safe assets only, which will direct impact equity returns and equity risk premiums.

1.2 LOSS AVERSION AND EQUITY RISK PREMIUMS

Loss aversion is attributed to psychological side of individuals decision making and, hence, to behavioural finance. Contrary to the efficient market hypothesis that states that "investment decision-makers (are) … rational, utility-maximizing individuals", investors are prone to acting under emotions (Singh, 2002). In an emotional state, individuals might make biased decisions via heuristic, and thus deviate from rational choice. In a financial market, deviation from rationality in investment decisions, especially by a large number of investors, may cause equity prices to deviate from their fundamental value, and therefore have a direct effect on equity premiums.

As highlighted by Duarte and Rosa (2015), and Damodaran (2012), the most critical factor in determining equity risk premiums is risk aversion. “As investors become more risk averse, equity risk premiums will climb, and as risk aversion declines, equity risk premiums will fall.” It is true that individual investors may have different levels of risk aversion, but taken on an aggregate level, changes in the collective risk aversion will manifest themselves in changes in equity risk premiums. Thus our choice of loss aversion specifically, out of many heuristics that influence investment decision-making, is justified by the fact that loss aversion is closely relates to risk aversion- individuals risk preference in choice under uncertainty, and hence equity risk premiums.

Schmidt and Zank (2005) in their discussion on the relationship of loss aversion and risk aversion state that majority of the observed risk aversion is due to loss aversion, “because loss attitudes seems to be an intrinsic component of risk attitudes.” Thaler et al (1996) in their experimental investigation of the role of loss aversion in rick aversion, assert that the experience of loss is the most important factor in inducing risk aversion. It is important to draw a clear distinction between risk aversion and loss aversion. Risk aversion is the behavior of rational economic agents in environments of uncertainty to reduce that uncertainty; it is the reluctance of an investor to purchase a risky asset with an uncertain payoff rather than a riskless asset with a possible lower expected payoff. Loss aversion on the other hand is the tendency of individuals (with limited rationality) to strongly prefer avoiding losses to acquiring gains; it is a heuristic investors use in making financial decisions that leads them to behave as if losses are twice as powerful as gains, in terms of their psychological effect. Loss averse investors (irrationally) forgo risky investments which would be accepted by rational economic agents otherwise, this reduced demand for risk impacts equity risk premiums directly and above, normal or rational investors risk aversion.

In sum, equity risk premiums are determined by the risk attitudes (risk aversion) of individual investors in the market. Also, loss aversion and risk aversion are concepts inherently related in choice under uncertainty, and both manifest in the investors preferences for risky gambles. The asymmetry of the effect loss aversion has on equity risk premiums in different parts of the business cycle create for a clear distinction of loss aversion heuristic, from rational expected utility risk aversion. Thus we can draw a direct link, with intuitive direction and magnitude of effect, between equity risk premiums and loss aversion heuristic of individual investors. The hypothesized relationship between loss aversion and risk premiums is as such, in a period of economic boom the coefficient on loss aversion heuristic should have negative sign with magnitude of about one, and in a recession this coefficient should have positive sing and be approximately twice as large as in magnitude then the boom period. It is exactly this link/intuition that this paper will exploit in order to investigate whether there is sufficient evidence to claim that Canadian equity premiums historically behave in a way consistent with the presence of loss aversion heuristic of individual investors, and thus contradicting the rationality of agents assumption of the EMH. Investigating the relationship between equity risk premiums and loss aversion is not straightforward since loss aversion is not directly observed in the data, so regular regression methods are disqualified. A creative way around this issue is to use Dynamic Factor Model (DFM) that allows to investigate the relationship of multiple time series with unobserved common factors, for our discussion purposes the unobserved factor is the loss aversion heuristic of individual investors.

Stock & Watson (2010) date the origins of DFMs to 1977 in the works of Geweke and, Sargent and Sims, who's work demonstrates a central empirical finding that a few factors can explain a large portion of variance in multiple macroeconomic time series.

In general, as described in Lütkepohl (2005) the dynamic factor models represent a vector of k endogenous observable variables, y_t, as linear functions of $n < k$ unobserved common factors, f_t, and idiosyncratic components, u_t. The model can be written as:

$$y_t = Lf_t + u_t,$$

where L is a $(K \times N)$ matrix of factor loadings, and the component of u_t are assumed to be uncorrelated, that is, the covariance matrix of u_t is diagonal. Some versions of the model allow for the unobserved factors, and the idiosyncratic components to be autocorrelated.

Since the study is interested specifically in the relationship between loss aversion and risk premiums, we will analyze multiple time-series of equity risk premiums of portfolios consisting of Canadian companies listed on the TSX stock exchange, to see how the unobserved factor, bias- loss aversion, affects the risk premiums in different parts of the business cycle.

Note that according to the theory of loss aversion, individuals risk tolerance or level of risk aversion, is affected by the previous dates changes in wealth. This implies that loss aversion heuristic will have different effects on individuals depending on their previous date changes in wealth, i.e. if an investor experienced a gain/loss of wealth in the previous period then he will be inclined to be more/less risk averse in the present period. To account for this aspect of loss aversion, and to be able to clearly distinguish the effect of loss aversion on equity risk premiums in both possible scenarios, we will estimate the coefficient on loss aversion in two separate time periods - a boom and a recession. For the purpose of keeping the study relevant and up to date the time window from 2005 -2012 is chosen, and divided into periods of boom 2005-2008, and recession 2008-12. As per our intuition we expect the coefficients' sings and magnitudes to be significantly different between the two periods.

As previously discussed, individual investors are more likely to be in an emotional state, and thus make biased decisions via heuristics, at a time of an unexpected and significant market events. To incorporate this aspect of psychology of individuals' investment decision, the closure of Lehman Brothers investment bank in the United States will be used as such event in the proceeding analysis.

2 DATA DESCRIPTION

The data used in this study consists of daily closing prices of 232 Canadian TSX listed companies for the period of September 2005 to September 2012, as well as the daily risk free rate for the same period. The reason the study focuses on Canadian TSX listed companies is because the intention is to concentrate on Canadian investors decisions. As highlighted by the works of Coeurdacier and Rey (2011), despite increasing global integration of financial markets, individuals are still "reluctant to reap full benefits of international diversification and hold disproportionate share of local equities." This phenomenon is referred to as the home bias, and has been documented in economic literature as early as 1991. According to Hau and Rey (2008), Canadian investors in the time window of our data set, were seen to hold more then 80% of domestic equity in their portfolio. Although this sample of Canadian equities does not provide a perfect representation of Canadian investors attitudes, it does give us a good indicator of the overall picture of attitudes in the Canadain markets, and thus a crude understanding of Canadian investors.

As mentioned previously, the data is divided into two subsamples; sample one consists of daily closing prices from September 2005 to mid September 2008, and sample two, from mid September 2008 to September 2012. The two samples are chosen to coincide with the business cycle fluctuations experienced by the Canadian market, as well as the disturbance caused by the unexpected and significant even defined earlier as the closure of Lehman Brothers investment bank in the United States.

2.1 PORTFOLIO FORMATION AND DATA MODIFICATIONS

Only Canadian companies that were listed for the whole duration of the sample were considered in the analysis. This allows us to compare the effect of loss aversion on the same equities in two different time intervals. Series with a small number of missing observations, less then ten missing observations, were treated by filling blanks with previous days closing price.

Since the study is aiming at exploring the relationship between loss aversion and risk premiums, the daily closing prices were converted, using first log difference, to daily rates of return. Additionally, to get to the daily risk premiums we subtracted the daily annualized risk free rate from each individual stock returns.

The portfolios were constructed by splitting up the 232 equities into 4 random portfolios of 54 equities each, and maximizing the Sharpe Ratio for each of the portfolios to get the necessary weight on each stock. Applying the optimal weight distribution to each portfolio, portfolio returns and premiums were then calculated and used for the analysis.

Additionally the data was normalized, this is necessary to avoid portfolios with larger inherit variations receiving more weight during the estimation. Thus normalizing the data guarantees that each portfolio is treated equally.

3 METHODOLOGY

In the present paper, the use of DFM is motivated by the Stock & Watson (1991) where the authors use multiple US macroeconomic time series to implicitly define a variable, to which they refer to as the overall state of the economy. Drawing parallels, this paper will use Canadian multiple time-series data, to implicitly identify individual investors bias, specifically loss aversion.

The structure of the analysis of this paper will follow closely the Stock & Watson (1991) methodology, mimicking the identification of 'Single-Index Model,' the State-Space representation, and the parameter estimation technique via Kalman Filter.

3.1 DYNAMIC FACTOT MODEL

The following notation will be used:

There are I portfolios indexed by i, and T time periods indexed by t.

Let $y_{i,t}$ denote the daily risk premium of portfolio i at time t.

At any given date t, each $y_{i,t}$ is comprised of two stochastic components: the common unobserved component or factor, f, and the idiosyncratic component, v_t. Both the unobserved factor and the idiosyncratic component are modeled as having linear stochastic structures, more specifically autoregressive processes of finite orders p and q, respectively. Formally the model is defined as:

(1) $y_{i,t} = \beta_i + \gamma_i f_t + v_{i,t}$

(2) $f_t = \varphi_1 f_{t-1} + \varphi_2 f_{t-2} + \cdots + \varphi_p f_{t-p} + \eta_t$

(3) $v_{i,t} = d_{i,1} v_{t-1} + d_{i,2} v_{t-2} + \cdots + d_{i,t-q} v_{t-q} + \varepsilon_{i,t}$

To ensure that the comovements of the multiple time series arise from a single source, f_t, it is assumed that the innovations, $v_{i,t}$, are mutually uncorrelated at all leads and lags, and the covariance matrix of $v_{i,t}$ is a diagonal i.e.,

$$Cov\left(v_{i,t}\right) = \mathrm{diag}(d_{i,1}(v_{t-1}), \dots, d_{i,q}\left(v_{t-q}\right))$$

and

$$E\begin{bmatrix}\eta_t \\ \varepsilon_t\end{bmatrix}[\eta_t \varepsilon_t'] \equiv \Sigma = \mathrm{diag}(\sigma_\eta^2, \sigma_{\varepsilon_1}^2, \dots, \sigma_{\varepsilon_I}^2)$$

In addition, we normalize the scale of f_t by setting $var(\eta_t) = 1$.

3.2 STATE SPACE REPRESENTATION

In order to estimate the model (1) - (3), we need to first transform it into a state space form, doing so allows us to evaluate the likelihood function using the Kalman Filter. The state space formulation has two parts: the measurement equation, which relates the observed variables to the unobserved state vector, and the transition equation, which describes the evolution of the unobserved state vector.

Using the notation of Lütkepohl (2005), for an observed multiple time series $y_1, \dots, y_T$ which depends on an unobserved state, z_t driven by a stochastic process, the measurement and transition equations, represented in state space form respectively, are given by:

(4) $y_t = \mathbf{H}_t z_t + v_t$

(5) $z_t = \mathbf{B}_{t-1} z_{t-1} + w_{t-1}$

where:

$\mathbf{H}_t$ and $\mathbf{B}_t$ are matrices that may depend on time, and v_t and w_t are error processes.

In our analysis, the measurement equation relates the portfolio risk premiums to the unobserved factor, and the transition equation describes the evolution of the unobserved factor.

Let Y_t, V_t, E_t, F_t, and N_t represent the vectors of the variables $y_{i,t}, v_{i,t}, \varepsilon_{i,t}, f_t$, and η_t. Then we can write our model in the general state space form as:

(6) $Y_t = \beta + Z\alpha_t$

(7) $\alpha_t = T\alpha_{t-1} + R\varsigma_t$

where:

$\alpha_t = (F_t', V_t')$

$\varsigma_t = (N_t', E_t')$

and where matrix T is a transition matrix, and Z and R are selection matrices. The covariance matrix of ς is $E\varsigma_t\varsigma_t' = \Sigma$.

3.3 ESTIMATION

Having constructed the state space equations, the Kalman Filter can be used to compute the Gaussian likelihood function for a set of parameters. Lütkepohl (2005) describes the filter as a tool for recursively estimate the state variable α_t, given observations $y_1, \dots, y_T$ of the output variables. Under normality assumptions, the estimator of the state produced by the Kalman Filter is the conditional expectation $E(\alpha_t | y_1, \dots, y_t)$, for $t > T$, the estimator $E(\alpha_t | y_1, \dots, y_T)$ is a forecast or prediction at the origin *T.* The filter also provides the conditional covariance matrix $Cov(\alpha_t | y_1, \dots, y_t)$ which may serve as a measure of estimation or for predicting uncertainty. The estimation of the state is called *filtering* to distinguish it from forecasting.

The filter consists of two sets of equations, the prediction and updating equations. The following notation will be used:

Let $\alpha_{t|t-1}$ denote the estimate of α_t based on $(y_t, \dots, y_{t-1})$,

$P_{t|t-1} = E\left(\left(\alpha_{t|t-1} - \alpha_t\right)\left(\alpha_{t|t-1} - \alpha_t\right)'\right)$, and recall that $E\varsigma_t\varsigma_t' = \Sigma$.

With this notation, the prediction equations of the Kalman Filter are:

(8) $\alpha_{t|t-1} = T\alpha_{t-1|t-1}$

(9) $P_{t|t-1} = TP_{t-1|t-1}T' + R\Sigma R'$

The forecast of Y_t at time *t-1* is $Y_{t|t-1} = \beta + Z\alpha_{t|t-1}$, and the forecast error is defined as $v_t = Y_t - \beta - Z\alpha_{t|t-1}$. Define the variance-covariance matrix of the forecast error as $F_t = E(v_t v_t') = ZP_{t|t-1}Z'$, then the updating equations are:

(10) $\alpha_{t|t} = \alpha_{t|t-1} + P_{t|t-1}Z'F_t^{-1}v_t$

(11) $P_{t|t} = P_{t|t-1} - P_{t|t-1}Z'F_t^{-1}ZP_{t|t-1}$

The Kalman Filter equations (8)-(11) allow for recursive calculation of the predicted state vector and of the covariance matrix of this estimate, given the assumed parameters in T, R, Σ, and Z, and given the initial values for $\alpha_{0|0} = 0$ and

$vec(P_{0|0}) = (I - T \otimes \mathrm{T}')^{-1} vec(\Sigma)$.

The Gaussian log likelihood is then computed as:

(12) $L = \frac{1}{2}\sum_{t=1}^{T} v_t' F_t^{-1} v_t - \frac{1}{2}\sum_{t=1}^{T} \ln\left(\det(F_t)\right)$

The Gaussian maximum likelihood estimates of the parameters are found by maximizing L over the parameter space.

4 RESULTS

Following the procedure of Stock and Watson (1991) the single-index model was constructed for the four portfolios, and represented in the state-space form so that the

Kalman filter could be applied. In the specification of the common unobserved factor, f_t, as well as the idiosyncratic component, $v_{i,t}$, a first order autoregressive process was adopted i.e., $p = 1$ and $q = 1$ respectively.

The single-index model for each of the portfolios is:

$y_{i,t} = \gamma_i f_t + v_{i,t}$ where, $i = 1,2,3,4$

$f_t = \varphi_1 f_{t-1} + \eta_t$

$v_{i,t} = d_{i,1} v_{t-1} + \varepsilon_{i,t}$

The results of the estimation of the coefficient are as follows:

Table : Parameter estimates of the model

Sample 2	*φ*	*γ_i*	*d_i*
Common factor	0.5209		
	(0.0406)		
	0.00 ***		
Portfolio 1		0.5498	0.0015
		(0.0326)	(0.0392)
		0.00 ***	0.969
Portfolio 2		0.6578	-0.1773
		(0.0227)	(0.0617)
		0.00 ***	0.00 ***
Portfolio 3		0.3194	-0.1164
		(0.0289)	(0.0325)
		0.00 ***	0.00 ***
Portfolio 4		0.3357	-0.1372
		(0.0290)	(0.0329)
		0.00 ***	0.00 ***

Sample 1	*φ*	*γ_i*	*d_i*
Common factor	0.2191		
	(-0.0532)		
	0.00 ***		
Portfolio 1		0.2967	0.1321
		(0.0425)	(0.1321)
		0.00 ***	0.00 ***
Portfolio 2		0.3302	0.0818
		(0.0420)	(0.0378)
		0.00 ***	0.03 **
Portfolio 3		0.6632	-0.251
		(0.037)	(0.4827)
		0.00 ***	0.00 ***
Portfolio 4		0.7406	-0.2777
		(0.0424)	(0.0562)
		0.00 ***	0.00 ***

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

The above table highlights the results of the estimation of the coefficients of the model. Intuitively, one would expect to see a change in the sign, and the magnitude of the effect between the two samples. As discussed earlier, in theory, loss aversion has a significantly different effect on risk premiums in different parts of the business cycle. When the markets are booming, investors experience gains in wealth and hence are more likely to take on risk, which drives the risk premiums down. On the other hand when markets are in recession, loss aversion would drive risk premiums up, by a magnitude approximately twice as large as the reduction of risk premiums in a boom. Thus in our first sample, the great moderation, we expected to see a negative coefficient on the loss aversion factor, which turned out not to be the case. All of the four portfolios are reported to have positive, and statistically significant coefficients on the loss aversion factor.

Looking at the results for the second sample, the estimated coefficients coincide with the intuition, when the markets are in a recession loss aversion is positively related to risk premiums. All four portfolios report a positive, statistically significant coefficient on the factor.

As mentioned previously, prior to estimation we normalize the scale of the factor by setting its variance to equal to one i.e., $var(\eta_t) = 1$. This has an effect on the absolute magnitude of the coefficient, thus our magnitude analysis will focus not on the magnitude of estimated coefficients, but rather variance decomposition, which we discuss next.

4.1 VARIANCE DECOMPOSITION

Based on the estimated model we can draw inference on how fluctuation in each individual portfolios risk premiums is effected by the variations in the common factor. By considering how much of the volatility of each individual portfolios risk premiums is explained by the variation of the common factor we can attach economic interpretation to the magnitude of the estimated coefficient reported above.

Recall the assumption made earlier that for each portfolio time series the common factor and the idiosyncratic component are mutually uncorrelated in all leads and lags i.e., they are orthogonal. In line with this assumption we can write each series variance as:

$$\sigma_i^2 = \gamma_f^{i^2} \sigma_f^2 + \sigma_{i,v}^2 \qquad \text{for } i = 1, \dots, 4$$

where:

σ_i^2 is the variance of each individual portfolios risk premiums, normalized to one

γ_f^i is the estimated coefficients on the common loss aversion factor

σ_f^2 is the variance of the common factor, loss aversion

$\sigma_{i,v}^2$ is the variance of each individual portfolios idiosyncratic component

Following Gregory, Head, Reynauld (1997), we compute estimates of R_f^i, which is the share of the variance of each individual portfolios risk premiums accounted for by the variation in the loss aversion factor; and is defined as follows:

$$R_f^i = \frac{\frac{\gamma_f^{i2}}{1-\phi_f^2}}{\frac{\gamma_f^{i2}}{1-\phi_f^2} + \frac{\sigma_{i,\varepsilon}^2}{1-d_{i,\varepsilon}^2}} \qquad \text{for } i = 1, \dots, 4$$

where $\sigma_{i,\varepsilon}^2$ is the estimated variance of the innovations of the idiosyncratic component of each portfolios risk premium. The results are reported below:

Table : Variance decomposition results

Sample 1		Sample 2	
Portfolio 1	10%	**Portfolio 1**	65%
Portfolio 2	10%	**Portfolio 2**	81%
Portfolio 3	67%	**Portfolio 3**	19%
Portfolio 4	86%	**Portfolio 4**	22%

An interesting observation is that in the first sample period, the variation of risk premiums in portfolios 1 and 2 are almost entirely attributed to the variation in the idiosyncratic component. This means that the variation in the common factor, loss aversion, had close to no effect on the changes in those portfolios risk premiums. While variations in risk premiums in portfolios 3 and 4 are largely attributed to the variation in the common factor. And this trend is reversed in the second sample period, where the exact opposite effects are observed.

Intuitively, we expected to see the magnitude of the effect of the common factor increase unilaterally in the second sample, in the neighborhood of twofold. The results turned out to be inconsistent with the intuition. We interpret these results as evidence to the contrary of existence of loss aversion heuristic in Canadian investors decisions. Risk premiums of the four portfolios appear to be following a random walk, rather then being uniformly influenced by the common factor.

A possible alternative interpretation is that the common factor captures more then just loss aversion heuristic and thus the estimated coefficients incorporate other components, which possibly overshadow the factors effect on the premiums. Another possible explanation for the inconclusive results of the analysis is that the portfolios themselves are inherently different. Since portfolio composition was random, no particular characteristic can be attached or used to differentiate between the portfolios. One common characteristic however, is that all companies in the sample were traded for the entire time interval of the sample. This implies that the more volatile and risky companies that went under during or after the recession are omitted from the analysis, and the sample is filled with companies fundamentally safer and better performing then the average firm during that time period. This may be a reason to believe that individual investors sentiment would have less affect on the fundamental value of these companies, and to the contrary, that these companies' fluctuations of risk premiums are driven by some economic fundamentals rather then individuals preferences.

5 SPECIFICATIONS TEST

We test the specification of our model in three particular areas, specifically, test of stationarity of the data, test for serial correlation of observed disturbances, and test if innovations are white noise. Checking these areas allows us to make sure that the model has been correctly specified, and thus provides us with a crude check for robustness of our results.

5.1 STATIONARITY of the data is an important aspect of the dynamic factor model, as well as the likelihood theory. A stationary process is a stochastic process in which the joint probability distribution i.e., mean, variance, and autocorrelation structure does not change through time. To test for stationarity an Augmented Dickey-Fuller (ADF) test was applied to each time series of the portfolios risk premiums in both sample periods. The results are reported below.

Table : ADF test results

Sample 1		**Sample 2**	
Portfolio 1	-12.992***	**Portfolio 1**	-16.176***
Portfolio 2	-12.239***	**Portfolio 2**	-13.649***
Portfolio 3	-16.003***	**Portfolio 3**	-18.502***
Portfolio 4	-16.013***	**Portfolio 4**	-16.889***

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

The results show no evidence, at the 1% critical value, that any of the four portfolios risk premiums in ether of the sample periods, are non-stationary.

5.2 SERIAL CORRELATION OF OBSERVED DISTURBANCES is another measure of the goodness of fit of our model. We assumed that all errors are uncorrelated in all leads and lags, and thus if the model is correctly specified then the serial correlation of the disturbances should be zero. On the other hand, the presence of serial correlation in the observed disturbances may be attributed to omission of relevant factors from the model or potentially to misspecification of the of the autoregressive structure of the factors.

To test for the presence of serial correlation in the idiosyncratic error, $v_{i,t}$, we define μ_i as the one-step ahead forecast error from the observed variables in the model i.e.,

$$\mu_i = y_t - y_{t|t-1}$$

where $y_{t|t-1}$ is the produced by the Kalman filter applied to our model.

In testing for serial correlation of observed disturbances, an F-test on the null hypothesis of joint insignificance of the coefficients of the one-step ahead forecast errors is performed. Note that both AR(1) and AR(2) lag structures for both the common and the idiosyncratic component are tested, results turned out to be nearly identical, and hence only results for the AR(1) process are reposted.

$H_0\colon \beta = 0$

$H_1\colon \beta \neq 0$

$\mu_{i,t} = \beta_i \mu_{i,t-1} + \cdots + \beta_p \mu_{i,t-p} + error$

The following tables reports the p-values for the regression coefficients:

Table : Serial correlation of observed disturbances test results

Sample 1

	dependent vars			
regressor	**μP1**	**μP2**	**μP3**	**μP4**
μP1	0.017**	0.010***	0.687	0.684
μP2	0.00***	0.385	0.014**	0.255
μP3	0.422	0.918	0.00***	0.635
μP4	0.505	0.588	0.607	0.00***

* significant at the 10% level

** significant at the 5% level

*** significant at the 1% level

Sample 2

	dependent vars			
regressor	**μP1**	**μP2**	**μP3**	**μP4**
μP1	0.764	0.98	0.674	0.158
μP2	0.006***	0.00***	0.831	0.00***
μP3	0.288	0.647	0.001***	0.94
μP4	0.04**	0.428	0.352	0.00***

As is evident from the tables, the null can be rejected for nearly half of the portfolios in both of the sample periods. For example, in the first sample, lagged portfolio one and two disturbances have statistically significant explanatory power of the portfolio one current risk premium. This implies that the disturbances in the observed variable are not uncorrelated in all leads and lags, contradicting our earlier assumption. This raises both a specification issue and potential source of bias in the results. Possible remedy could be to increase the lag structure of errors, or include lags of the estimated factor in the regression equation; both are left as a possible topic of future research.

5.3 ARE INNOVATIONS WHITE NOISE

We investigate whether the innovations, $\varepsilon_{i,t}$, are white noise and random in an attempt to check the validity of our models assumptions. The idea is to see if the data exhibits correlations that are significantly different from zero. Non-randomness of residuals could be viewed as evidence of model misspecification, specifically that the AR(1) lag structure of the idiosyncratic component is not sufficient to account for the serial correlation in the data. A Portmanteau test is conducted to test for the randomness of the innovations.

$H_0: errors\ are\ white\ noise\ (random)$

$H_1: erros\ are\ not\ random$

The results are reported below:

Table : Portmanteau test results

Sample 1	Q- stat	Prob>chi^2
Portfolio 1	74.4839	0.0008***
Portfolio 2	84.5086	0.0001***
Portfolio 3	45.1692	0.2648
Portfolio 4	33.6023	0.7523

Sample 2	Q- stat	Prob>chi^2
Portfolio 1	43.395	0.0000***
Portfolio 2	106.0599	0.0000***
Portfolio 3	1.9374	0.3796
Portfolio 4	8.6873	0.013*

* significant at the 10% level

** significant at the 5% level

*** significant at the 1% level

The results indicate that the innovations are not random. In the first sample period, portfolios 1 and 2 display persistent correlation in the disturbances, which is statistically significant at the 1% level. This result is consistent with the previous serial correlation test, where we've seen that for the first sample, the disturbance of portfolio 1 could be forecasted by lagged disturbances of itself and portfolio 2. Similar results are observed for sample 2, where we see that only randomness in portfolio 3 innovations is failed to reject at the 5% level. This again brings light to issues with specification of the model, and evidence to overly strict assumptions, which are not supported by the data.

Note that Portmanteau test with AR(2) lag structure was also conducted, results of which were insignificantly different from the AR(1) specification, and hence are omitted here. The implications of these results is that further modeling beyond AR(2) process of the idiosyncratic component of the model is necessary for more desirable results. However such alternations of the model are not conducted here due to modeling and computational limitations, but are brought up as a possible future area of research.

6 CONCLUSION

Major global economic events can shape our understanding of economic theory, financial markets, and the effects of individuals attitudes and decisions on economic environment. In order to improve our understanding of market processes and the effects of individuals' decisions on these processes, it is essential that we study historic events in order to extract all possible lessons. In the recent past, the Great Recession of 2008, has provided us with an opportunity to improve our understanding of risk, market efficiency, and possible relationship between psychology of individuals investment decisions, risk preferences, and risk premiums. As has been discussed in this paper, individuals' market decisions have the potential to influence the fundamental value of assets, and furthermore risk premiums and market efficiency.

One of the main criticisms of the efficient market hypothesis is that it does not account for the possibility of irrational investors. It is well documented that investors, as all humans, are prone to making biased or irrational decisions while in an emotional state. Since bias is not directly observed and difficult to quantify, an alternative approach to regular regression methods is required to evaluate its relationship with risk premiums. The dynamic factor model framework is of particular use here because it allows us to use multiple time-series to extract an unobserved common component, our individuals' bias, as the primary driving force behind the variation in the series.

The results of the analysis show inconclusive evidence of presence of loss aversion heuristic in the Canadian equity market. Though the estimates of the coefficient of the model are statistically significant, the magnitude and direction of the effect are not consistent with theory and intuition. The data on Canadian equity risk premiums therefore supports the Efficient Market Hypothesis theory; in that there's no clear evidence that equity risk premiums are significantly influenced by a common bias factor, and are not following a random walk. As well as, there is no evidence to support the assertion that Canadian investors display characteristics of loss aversion heuristic, and therefore no evidence to support the limitation on rationality of investors, as prescribed by prospect theory.

Lastly, the specification tests show inadequate results for approximately half of the sample, this raises issues with both the effectiveness of the model to map out the relationship between individuals investors bias, loss aversion, and risk premiums and, the validity of the estimates. Expanding the model to correct these specification issues is computationally expensive and outside the scope of this paper, and is brought up here only as possible areas of future research.

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