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ABSTRACT

We use traded options on growth and value indices to test for clientele differences in risk preferences. Value investors appear to have exhibited a higher average level of risk aversion than growth investors for two different time periods in the late 1990's and early 2000's. We construct a model of time-varying clientele preferences that allows investors with different levels of risk-aversion to switch between investment styles conditional upon the evolution of returns and risk. The model makes predictions about the autocorrelations structure of measured risk parameters and also about the autocorrelation and cross-autocorrelation of fund flows by style. Empirical tests of the model provide evidence consistent with the existence of style switchers—investors who move funds between growth and value securities. We construct trading strategies in the value and growth index options markets that effectively buy risk from one clientele and sell it to another. These strategies generated modest positive returns over the period of study.

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I. Introduction

Modern asset pricing theory is predicated on an integrated market for risk, however, clientele effects represent an interesting and important challenge to this neo-classical framework. In certain circumstances, investment clienteles appear to segment the market, creating apparent opportunities for arbitrage in expectations. The widely-documented S&P 500 listing return is a clientele effect. Buying in advance of a previously announced listing generates positive returns on average and selling in advance of a previously announced delisting avoids negative returns on average. This is apparently the result of a sudden and predictable shift in the clientele for a specific security.

Clientele effects are of great interest to research in behavioral finance. Barberis, Shleifer and Wurgler (2005), for example, attribute the S&P 500 listing effect to a combination of frictions and sentiment. Grinblatt and Han (2005) and Goetzmann and Massa (2004) show that the prevalence of disposition-prone investors holding a certain stock can have price effects. Lamont and Thaler (2003), examining "tech-bubble stubs," explain deviations from the law of one price by a segmented market for equity claims: one segment being investors irrationally eager to hold "hot" stocks. Kumar and Lee (2005) identify clienteles for growth vs. value stocks using a large database of individual accounts and find evidence suggesting that differing clientele sentiment is a potential determinant of returns. In a theoretical framework, Barberis and Shleifer (2003) show how partly segmented markets can be sustained by communities of investors focused on sub-sets of the investment universe. In their model, sub-sets of investors co-ordinate purchases and sales of style portfolios based upon past returns as a common signal. These dynamic decisions sustain excess co-movement among sub-sets of securities. While the asset return dynamics in their model are an interesting consequence of clientele effects, the implications for investor sub-set characteristics is also interesting from the perspective of behavioral finance. Their model, in effect, implies slightly differing representative investors.

In all of these examples, the price of an asset – and hence the implicit price of the risk characteristics of that asset – is affected by differing investor characteristics. This is both a necessary feature of behavioral studies and a significant empirical problem. The problem is that it is hard to distinguish among groups based upon measurable psychological features and tendencies. For example, it would be useful to characterize investor clienteles according to their risk attitudes. One could thus test the proposition that clientele risk preferences could affect prices for sub-sets of stocks – in effect segmenting the market. In this paper we use traded derivatives on equity indices to explore this approach.

Evidence on risk preferences is of particular interest because risk represents the foundation of asset pricing theory and the definition of capital market integration – i.e. that a unit of risk exposure in one market commands the same compensation as a unit of risk exposure in another. While investor preferences are an important bridge that joins risk exposure and returns, only limited empirical evidence exists on the risk preferences of investors in different assets.

In this paper, we use the prices of options on five major value and growth indices to study the risk preferences of investors in value and growth indices and their derivatives. The indices we use are widely followed benchmarks for value and growth investment styles, and include *The Standard & Poor's Barra Growth and Value Indices*; *Russell Midcap Growth and Value Indices; Russell 1000 Growth and Value Indices; Russell 2000 Growth and Value Indices;* and *Russell 3000 Growth and Value Indices*.

First, we extract latent risk aversion coefficients from the prices of derivative securities traded on these indices over two windows in time: 1996 through 1998 and 2002 through 2005. These windows are limited by the availability of options data on the indices, but never-the-less provide evidence over differing market environments. We adopt a flexible methodology for estimating the clientele risk aversion coefficient that does not assume a specific form for the utility function. We then test whether investors in different styles differ with respect to their risk preferences. We find some evidence that they do. Investors in value indices (and their derivatives) over the periods of study displayed higher implicit risk aversion than investors in growth indices (and their derivatives). We thus identify *risk preferences* as a potentially important attribute that categorizes differences across the two investor clienteles. The difference in average risk posture across the representative investors in these different sets of assets is, in itself, an interesting result. While other work on style and clientele effects has shown that sentiment may play an important role in defining clienteles, (e.g. Kumar and Lee, 2005) we find that risk is also potentially salient. Our findings thus not only support previous empirical evidence on style-based clienteles, but add to the understanding about what differentiates them.

We also find that estimated preferences exhibit different time series patterns. The risk preferences of value investors exhibit stronger persistence in the time series. This suggests that investors in value funds may be a more stable clientele than investors in the growth funds. The time series patterns in estimated measures of risk preferences also suggest the presence of *switchers*—investors who move between the two styles. We find evidence consistent with the hypothesis that high past style returns attract switchers to that style. We also find evidence that past returns and risk on a competing style may attract switchers away from a given style. For example, high recent returns on a growth index may cause some investors to sell shares in value funds and buy shares in growth funds. Recent changes in the volatility of index returns are also associated with evidence of style switching. This is consistent with findings in the mutual fund flows literature, where evidence suggests that some investors enter (and exit) the market when volatility changes.[1]

We also examine the behavior of investors using data on purchases and sales of mutual funds that are explicitly identified with growth and value styles. We use data on aggregate flows to the value and growth mutual funds in the U.S. to study the contemporaneous and lagged response of investor flows in the growth and value styles. The data is from TrimTabs for the period from February 1999 through November 2006. The data covers flows to a representative selection of mutual funds in Growth and Value Morningstar categories.[2]

We find that time series patterns in fund flows match those of estimated risk preferences. Aggregate flows to value funds display a pattern of stronger persistence than aggregate flows to the growth funds. Autocorrelation in flows to value funds is higher in magnitude than in the case of growth investors and it remains positive at a longer horizon. This pattern is the same in the time series of estimated risk aversion.

We also find evidence of switching behavior in the fund flows. High past returns on a style attract flows to that style. For example, flows to the growth style increase with returns on the growth style and decrease with returns on value. Examination of fund flows reveals patterns consistent with the presence of switchers who follow returns. Overall, results obtained from mutual fund flows support the conclusions made from estimated risk aversion coefficients.

[1] Goetzmann and Massa (2002).

[2] To study the behavior of investors we also use data on flows at the level of individual mutual funds. Our data set includes a panel of individual mutual fund accounts for Kemper mutual funds for five years, 1995 through 1999. The particular advantage of the Kemper data set is that the disaggregate account-level information allows us to identify fund clienteles. The results from this dataset support those found in the aggregate flow data.

Finally, we test whether the market for risk across growth and value funds is integrated by constructing a trading strategy that, in effect, buys risk in one market (where it is cheap) and sells it in another (where it is dear). If the market for risk is segmented between growth and value index investors, this has the potential to be a profitable strategy. Despite data limitations, we find some evidence that this arbitrage in expectations reflects a segmented market.

The paper is structured as follows. In Section II we lay out the analytical framework for the analysis and the testable restrictions. Section III describes the data and methodology. In Section IV we report empirical results. Section V describes evidence from mutual fund flows. Section VI studies trading strategies. Section VII discusses the implication of the results. A brief conclusion follows.

II. Analytical Framework

In this section we discuss a framework similar to that of Barberis and Shleifer (2003). We do not develop a full theoretical model to explain the existence of style investing, but rather we use growth vs. value styles in the U.S. equity market as a basic structure for identifying investor clienteles. Following Barberis and Shleifer (2003), the common feature of style investing is that investors aim to hold securities that have a common pre-defined characteristic, such as a high book-to-market ratio for value investing, or high expected growth for the growth style. In this section we explore the implications of this kind of style investing for an empirical study of risk preferences.

We consider investors who trade in value (growth) funds and their derivatives, and refer to them as value (growth) investors. In addition to these two clienteles, we also consider switchers—a clientele of investors who trade in both types of funds and, in effect, move between the two styles depending on the recent relative risk and return characteristics of the two styles. The framework allows for individuals who invest in both funds simultaneously, but, under reasonable assumptions about their preferences, this has the empirical effect of lowering test power, rather than changing the implications of the framework. We assume that all investors have CARA preferences, and all investors have identical wealth.[3] In the case of negative

[3] The qualitative results in this section do not depend on these assumptions. The assumptions are made merely for tractability.

exponential utility, the risk aversion of the representative investor is the wealth-weighted harmonic mean of the risk aversions of the individual investors.[4] We now characterize a representative investor in each style.

Let there be K investor types that invest in a value fund (not including the switchers). These K types have different levels of risk aversion, $a_{V,1} \le a_{V,2} \le \ldots \le a_{V,K}$, and there are $n_{V,j}$ investors with risk aversion $a_{V,j}$. There is a total of n_V investors,

$$n_V = \sum_{j=1}^{K} n_{V,j} .$$

When these are the only investors in a value fund, the representative investor has risk aversion a_V defined as,

$$\frac{1}{a_V} = \frac{1}{n_V} \cdot \sum_{j=1}^{K} \frac{n_{V,j}}{a_{V,j}} .$$

The risk aversion of the representative investor in a growth fund can be similarly defined from,

$$\frac{1}{a_G} = \frac{1}{n_G} \cdot \sum_{j=1}^{L} \frac{n_{G,j}}{a_{G,j}}, \qquad n_G = \sum_{j=1}^{L} n_{G,j} ,$$

where there are L types that invest in a growth fund (not including the switchers), with risk aversion coefficients, $a_{G,1} \le a_{G,2} \le \ldots \le a_{G,L}$; there are $n_{G,j}$ investors with risk aversion $a_{G,j}$.

Let $i \in \{V, G\}$ represent value and growth styles. We now consider a case in which, in addition to the types of investors described above, switchers are also present in the style clientele i. All switchers have risk aversion a_S, and the number of switchers who are invested in style i is $n_{S,i}$. Then, risk aversion of the representative agent in style i, denoted $a_{R,i}$, is given by,

$$\frac{n_{S,i} + n_i}{a_{R,i}} = \frac{n_{S,i}}{a_S} + \frac{n_i}{a_i} = \frac{n_{S,i}}{a_S} + \sum_j \frac{n_{i,j}}{a_{i,j}} . \qquad (1)$$

Equation (1) shows that the risk aversion of the representative agent in a style, $a_{R,i}$, depends on the composition and the relative number of investors who focus on that style, n_i, and the number of switchers present $n_{S,i}$. If the composition changes because the number of an investor type changes, there will be a change in risk aversion of the representative agent within that style

[4] See Ingersoll (1987), Chapter 9, for a discussion of utility aggregation.

clientele. For example, if an increase in the risk of a style causes some investors with high risk aversion values $a_{i,j}$ to leave that style, then the number n_i will decrease and the relative number of switchers in the style will be higher.

We maintain, and later test empirically, the assumption that different clienteles differ in their average[5] risk aversion, $a_S \le a_G < a_V$. Note that results that follow *do not* require that switchers have a lower risk aversion than a growth investor with the smallest risk aversion. In other words, we do not require $a_S \le a_{G,1}$. The requirement is weaker, $a_S \le a_G$. Also, we *do not* require the growth investor with the highest risk aversion to have risk aversion lower than the value investor with the lowest risk aversion. We do not require $a_{G,L} \le a_{V,1}$. The requirement is weaker, that, *on average*, $a_G < a_V$.

Put differently, we do not require that growth investors only invest in the growth style, or that value investors only invest in the value style. In this setting, the sets of growth and value investors are not disjoint, and a growth investor can invest in both growth and value styles, just as a value investor can hold both value and growth securities. The growth investors own *predominantly* growth securities, and the value investors invest *mostly* in value index. This means that in our analysis we do not imply or require that growth style is owned only by the growth investors, or that the value style is owned only by the value investors. Testable hypotheses developed in this section are based on a setting where the requirement is weaker. *On average*, the investors in a growth index are growth investors. And on average the investors in the value index are value investors.

Having defined the risk aversion of the representative agent, we now turn to a discussion how switching between styles will impact the risk aversion of the representative agent. First, we study the case in which switchers react to returns. Then, we study the case in which switchers react to risk (volatility).

Switchers React to Returns

We begin with the case in which switchers allocate funds to a style depending on that style's past performance relative to the other style. This is the case of the positive feedback style switchers in the Barberis and Shleifer (2003). When deciding on their allocation, switchers

[5] Where average is defined explicitly as a wealth-weighted harmonic mean.

compare style X's and style Y's past returns. They then move into the style with the better recent performance, and move out of the other style. When this takes place, it affects the composition of investors in both styles and the risk aversion of the representative investor in that style clientele. High returns on a style attract switchers with low risk aversion to the style and therefore lowers the risk aversion of the representative investor. A high return on a *competing style* attracts switchers away from a given style and results in an increase in the risk aversion of the representative investor. For example, a high return on the value index attracts switchers away from growth and results in an increase in the risk aversion of the representative investor for growth.[6]

This is a testable hypothesis. A change in the risk aversion of the representative investor in a style should be *negatively* related to the past return on that style, and *positively* related to the past return on the alternative style. For example, in a regression of a change in the risk aversion of the representative investor in a growth index on past returns of growth and value indices, we would expect the coefficient on the growth index return (return on the same style) to be negative and the coefficient on the value index return (return on the alternative style) to be positive. Support for this hypothesis would thus provide support for the existence of switchers.

Reaction to Volatility

In addition to taking past returns into account when making decisions to invest in a style, investors may also take risk into account. Goetzmann and Massa (2002) study investors in S&P 500 Index mutual funds and their response to changes in the volatility of the S&P 500. The results suggest that individual investor behavior may be conditioned upon risk. They identify a group of "volatility chasers"—investors that enter the fund when volatility increases. They also show that there is a different group that exits the fund when volatility increases. In this section we study the implications of such reactions to volatility for a study of risk preferences.

We maintain our main assumptions in this section. We characterize a change in the risk aversion of the representative agent in a style caused by a change in volatility sufficiently large

[6] The result is related to the fact that harmonic means are never larger than arithmetic means and are lower unless every component in the average is the same. Therefore, the risk aversion of the aggregate, or representative, investor is less than the average of risk aversions, and, other things being equal, investors with a lower risk aversion have a greater influence on the risk aversion of the representative investor.

to cause some investors to enter the style, and some to leave. The change in risk aversion of the representative investor in style $i \in \{V, G\}$ is given by the total differential of (1),

$$da_{R,i} = \frac{\partial a_{R,i}}{\partial n_i} dn_i + \frac{\partial a_{R,i}}{\partial n_{S,i}} dn_{S,i} .$$

In the case of switchers who are chasing the volatility, following an increase in volatility, there is an inflow of switchers, so that $dn_{S,i} > 0$. If, at the same time, an increase in volatility leads some investors in the style to leave, then $dn_i < 0$. The expression for the total differential is,

$$da_{R,i} = \frac{a_i \cdot a_S \cdot (a_i - a_S)}{(a_S n_i + a_i n_{S,i})^2} \left[n_{S,i} \cdot dn_i - n_i \cdot dn_{S,i} \right]. \qquad (2)$$

The last expression leads to several observations. The first observation is that *if the risk aversion of investors in the given style is equal to the risk aversion of the switchers,* $a_i = a_S$ *then there will be no change in the risk aversion* $a_{m,i}$; $a_i = a_S$ implies zero change $da_{R,i} = 0$. This result is intuitive. The risk aversion of the representative investor is the harmonic mean. When switchers are the same as other investors, switchers who leave the index (or enter) do not affect the average. A related observation is that if the difference in risk aversions for the given style clientele and for the switchers is small— i.e. if the two numbers are very close in value, $a_i \approx a_S$, then we will observe a small change in the risk aversion of the representative investor in the style.

The second observation is that when $a_i \neq a_S$, *an increase in volatility will lead to a decrease in risk aversion*—the change is negative, $da_{R,i} < 0$. To show this, observe that the first term on the right-hand-side of (2) is positive. The second term in (2), in square brackets, is negative because $n_S \cdot dn_i < 0$ (investors leave upon increased volatility), and $-n_i \cdot dn_{S,i} < 0$ (switchers enter). Hence, $da_{R,i} < 0$. This is a testable hypothesis.

The third observation relates to the relative magnitude of the effect for different styles. Under a few simplifying assumptions, we show that when the risk aversion coefficients of switchers, growth investors, and value investors are ranked as $a_S \leq a_G < a_V$, *the change in risk aversion of the representative investor in the growth index is smaller in absolute value than the* *change in risk aversion of the representative investor in the value index.*[7] In other words, the impact on the risk aversion in the value index will be larger in magnitude, holding all else equal. Using our notation, $\left|da_{R,G}\right| < \left|da_{R,V}\right|$. This also is a testable hypothesis.

Impact of Style Switching on Risk Aversion

In the previous section we showed that investors who react to volatility will have an impact on the risk aversion of the representative investor in each of the two styles. The impact will be larger in magnitude for the value index. The focus is on the asymmetry of the effect. The same number of switchers entering a style will cause a larger change in the case of value index. The analysis does not require that volatility switchers leave one index and enter the other simultaneously, each style can be analyzed separately.

We now consider the impact of style switching where the switchers leave one of the two styles (for example, growth) and enter the other style (value). Only the switchers change between styles, so that $dn_i = 0$, $dn_{S,G} = -dn_{S,V}$, and the change in risk aversion is

$$da_{R,i} = -\frac{a_i \cdot a_S \cdot \left(a_i - a_S\right)}{\left(a_S n_i + a_i n_{S,i}\right)^2} n_i \cdot dn_{S,i} .$$

The first result is that, because switchers change between styles ($dn_{S,G} = -dn_{S,V}$), there is a negative relation between changes in risk aversion for the two styles, $da_{R,G} = -da_{R,V}$.

The second result is that changes in risk aversion in the two styles will be different in magnitude. When the risk aversion coefficients of switchers, growth investors, and value investors are ranked as $a_S \le a_G < a_V$, *the change in risk aversion of the representative investor in the growth index is smaller in magnitude (in absolute value) than the change in risk aversion of the representative investor in the value index,*[8] $\left|da_{R,G}\right| < \left|da_{R,V}\right|$. When switchers switch between the two styles, we expect that, on average, there will be a larger impact on risk aversion for value than on risk aversion for growth.

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[7] We discuss the assumptions and provide a proof in Appendix A. In essence, for tractability we require that two styles are equal in size and that when volatility increases, the changes in the number of investors in the two styles are equal, too. The result is stated in absolute value terms because the change is negative for both styles.

[8] The proof is in Appendix A.

In this section we developed several implications that style investing has for a study of risk preferences. In order to test the above predictions, we proceed as follows. First we estimate the risk preferences of investors in value and growth funds. Next, we identify differences among value and growth investors. Then, we study how changes in the estimates of risk preferences relate to past risks and returns on the two styles.

III. Methodology and Data

Our study is based on a well-known relation between investor preferences, risk-neutral probabilities, and actual probability densities. In particular,

$$U_t'(S_i,T)\cdot Q_t(S_i,T)\propto P_t(S_i,T),$$

where $P_t(S_i,T)$ and $Q_t(S_i,T)$ are the time-t risk neutral and subjective (true, or actual) probability distributions of return on S_i at time T, respectively, and $U_t'(S_i,T)$ is the time T marginal utility. Differentiating the above with respect to S_i, and dividing by the same equation yields:

$$\frac{Q_t'(S_i,T)}{Q_t(S_i,T)}+\frac{U_t''(S_i,T)}{U_t'(S_i,T)}=\frac{P_t'(S_i,T)}{P_t(S_i,T)}$$

Rearranging yields the following expression for the risk aversion coefficient,

$$Risk\ \ Aversion=-\frac{U''(S_i,T)}{U'(S_i,T)}=\frac{Q'(S_i,T)}{Q(S_i,T)}-\frac{P'(S_i,T)}{P(S_i,T)}, \qquad (3)$$

Note that risk aversion is locally identified from the shapes of the risk-neutral and actual PDFs.[9]

To determine the two distributions, we combine the methodologies of Bliss and Panigirtzoglou (2002, 2004) and Jackwerth (2000). Using option prices for a particular underlying index, we estimate the risk-neutral probability density function (PDF) according to Bliss and Panigirtzoglou (2002, 2004). We then use five years of past monthly index returns to determine a risk-adjusted (or, subjective) PDF using a nonparametric kernel density estimator similar to the one used in Jackwerth (2000). Risk aversion is the adjustment required to

[9] Methods for extracting risk preferences from option prices are studied by Jackwerth (2000), Jackwerth and Rubinstein (1996), Aït-Sahalia and Lo (1998, 2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2002, 2004), Rosenberg and Engle (2002).

transform the risk-neutral PDF into the risk-adjusted PDF. Using this method, the risk aversion coefficient can be estimated for every trading day for any asset for which option prices are available.

We perform numerous robustness checks to study sensitivity of our results to the choice of five years of past returns for the construction of subjective PDFs. In the first robustness check the true distribution is estimated using returns that are lagged by 6 months relative to the date when risk aversion is estimated, compared to the one month lag used in the standard procedure. In the second robustness check the entire previous history of growth and value returns, going back to 1926, is used to form the subjective distribution. This is the case when investors form their assessment of the return distribution based on the entire previous history of growth and value returns. In another robustness check we investigate the effect of the recent technology bubble and the subsequent crash. We exclude the bubble period and use the entire history of prior growth and value returns for the periods 1926 – 1996 to construct subjective distribution. These experiments provide an empirical basis for evaluating the robustness of the risk-preference extraction methodology. We find that the results are virtually unchanged by these adjustments.

A. Risk-neutral Probability Distribution

One method for finding the monthly risk-neutral distribution is proposed in Jackwerth and Rubinstein (1996). The method is based on a search for the smoothest risk-neutral distribution, which at the same time explains option prices. The trade-off between the two contradicting goals is exogenously specified. Three main issues arise with this approach (Jackwerth 2000). First, matching the option prices by minimizing squared errors puts more weight on in-the-money options compared to out-of-the-money options. Second, the Jackwerth-Rubinstein method does not account for microstructure effects. At-the-money option prices vary less throughout the day than away-from-the-money options. Third, the Jackwerth-Rubinstein method uses the integral of squared curvature of the probability distribution as a measure of smoothness.

We use a different approach that addresses some of these technical issues. We know from option pricing theory that the risk-neutral PDF is embedded in option prices. Let T be the expiration date of an option. The PDF, $f(S_{i,T})$, for the underlying asset i at time T has been shown to be related to the price of the European call option, $C(S_{i,t}, K, t)$.[10] Here, K is the option strike price and $S_{i,t}$ is the price of underlying i at time t where $t<T$. This relationship is:

$$f(S_{i,T}) = e^{r(T-t)} \frac{\partial^2 C(S_{i,T}, K, t)}{\partial K^2}\bigg|_{K=S_{i,T}}.$$

For each underlying asset, i, and for each expiration date, however, the function $C(S_{i,t}, K, t)$ is unknown and only a limited set of call options with different strike prices exist. Therefore, in order to calculate the second derivative we estimate a smoothing function using option prices with different strike prices but with the same expiration dates.

Instead of estimating such a smoothing function in option price/strike price space, we follow Bliss and Panigirtzoglou (2002, 2004) by first mapping each option price/strike price pair to the corresponding implied volatility/delta. We fit a curve connecting the implied volatility/delta pairs using a weighted cubic spline where the option's vega is used as the weight. We take 300 points along the curve and transform them back to the option price/strike price space. We thus obtain a smoothed price function, which we numerically differentiate to produce the estimated PDF. Bliss and Panigirtzoglou (2002) find that this method of estimating the implied volatility smile and the implied PDF is quite robust.[11]

A weighted natural spline is used to fit a smoothing function to the transformed raw data. The natural spline minimizes the following function:

$$\min_{\theta} \sum_{j=1}^{N} w_j \left(IV_j - IV(\Delta_j, \theta)\right)^2 + \lambda \int_{-\infty}^{\infty} g''(x;\theta)^2 dx,$$

where we omit the security-identifying index, i, for brevity; IV_j is the implied volatility of the j^{th} option on security i in the cross section; $IV(\Delta_I, \theta)$ is the fitted implied volatility which is a function of the j^{th} option delta, Δ_j, and the parameters, θ, that define the smoothing spline, $g(x;\theta)$; and w_j is the weight applied to the j^{th} option's squared fitted implied volatility error. Following Bliss and Panigirtzoglou (2004), in this paper we use the option vegas, $\nu \equiv \partial C / \partial \sigma$, to weight the observations. The parameter λ is a *smoothing parameter* that controls the tradeoff

[10] Breeden and Litzenberger (1978).
[11] This procedure does not require that Black-Scholes option pricing model hold (Bliss and Panigirtzoglou 2004).

between goodness-of-fit of the fitted spline and its smoothness measured by the integrated squared second derivative of the implied volatility function.

From the estimated cubic spline curve, we take 300 equally spaced deltas and their corresponding implied volatilities and transform them back to option price/strike price space using the Black-Scholes option pricing formula that accounts for dividend payments and using the dividend yield for the index. However, although the deltas are equally spaced, the strike prices that are obtained after the conversion are not. We use a cubic spline for a second time to fit a curve connecting the 300 unequally spaced call price/strike price pairs. This allows us to choose 300 equally spaced strike prices with their corresponding call prices.[12] Finally, we use finite differences to estimate the second derivative of the call price with respect to the strike price. This yields the risk-neutral PDF. This procedure does not depend on a specific option pricing model (Bliss and Panigirtzoglou 2004).

B. Subjective Probability Distributions

We use a kernel density estimator to estimate the subjective (risk-adjusted) probability density functions. A similar procedure is used in Jackwerth (2000).[13] We use the most recent 60 months of return data to estimate the risk-adjusted distribution. For example, to find estimates for January 1996, we use monthly return data from January 1991 to December 1995. All information used in the calculation is part of the investors' information set. Other windows were considered but results were highly correlated. For example, we tried a window of past returns with a lag of one year or six months, and we tried using 72 months of returns instead of 60. Varying our initial choices does not change the results.

We calculate monthly non-overlapping returns from our 5-year sample and compute the kernel density with a Gaussian kernel. The bandwidth

$$h = \hat{\sigma}\left[4/(3n)\right]^{1/5},$$

[12] 1. This problem is similar to all problems with missing prices, and the approach taken is similar to matrix pricing used for fixed income securities. The procedure we use is similar to Bliss and Panigirtzoglou (2004).

[13] This is different from Bliss and Panigirtzoglou (2004) who first hypothesize a utility function (power and exponential utility) for the investor and then use this function to convert the risk-neutral PDF to the subjective PDF. We do not follow this approach because we do not hypothesize a utility function.

where h is the kernel bandwidth, $\hat{\sigma}$ is the standard deviation of the sample returns, and n is the number of observations, is selected according to the recommendation in Jones, Marron and Sheather (1996).

C. Data: Estimation of Risk Preferences

We identify five value-growth index pairs for which call options are traded. Table 1 lists the index pairs and the dates when daily option prices are available. Our study covers major value and growth indices: *The Standard & Poor's Barra Growth and Value Indices*; *Russell Midcap Growth and Value Indices; Russell 1000 Growth and Value Indices; Russell 2000 Growth and Value Indices;* and *Russell 3000 Growth and Value Indices*. In addition to the daily closing option prices, we use monthly index returns and daily index closing prices. Summary statistics for the indices in the sample is given in Table 2. The table provides risk and return characteristics of the indices: annualized average return, standard deviation, Sharpe ratio, and total value of $1 invested in the index (total dollar return).

To estimate risk aversion we need prices of options with different strike prices written on the indices in the sample. Similarly to Jackwerth (2000), we estimate risk aversion with a constraint on the money-ness. Jackwerth only considers options such that the ratio of the strike price to the underlying index value is between 0.84 and 1.12. This procedure eliminates far-away-from-the-money observations. This may cause a problem of missing observations, but only when there are large movements in the underlying index value.

Options on equity indices generally exist with expiration dates at the nearest months, and at three-month intervals.[14] For example in the month of December there are options on the *Russell Midcap Growth* and *Value* indices that expire in December, January, February, and June. For our estimation we consider options that expire between one and four months from day t. We use this approach to maintain a relatively constant horizon for our analysis, and at the same time to have a sufficient number of option contracts to obtain reliable risk aversion estimates.

For each trading day we estimate the risk aversion for five value indices and five growth indices. We also use options on the S&P 500 Index (symbol: SPX) and on S&P 100 Index (OEX) to estimate risk aversion for the market. On each date we calculate estimates of Arrow-

[14] See Battalio, Hatch, and Jennings (2004), and Mayhew and Mihov (2004) for the description of the equity options markets including institutional background.

Pratt risk aversion functions across wealth using (3), a computationally intensive process. We compute the average of daily estimates within a month to obtain monthly estimates of risk aversion. We also compute the standard deviation of the daily estimates.

D. Data: Mutual Fund Flows

We use data on mutual fund flows to value and growth funds to study investor behavior. Our data set is obtained from TrimTabs and consists of daily mutual fund flow data for mutual funds in the following nine categories: Value funds (small, medium and large market capitalization); Blend (small, medium and large capitalization); and Growth funds (small, medium and large capitalization). We add daily flow data within a month to construct monthly flows to growth and value funds from February 1999 through November 2006. TrimTabs data represents aggregate flows to these fund categories.

We also use two data sets on flows to individual growth and value mutual funds. The first data set includes a panel of all individual mutual fund accounts for Kemper mutual funds for five years, 1995 through 1999. We use the individual account data to compute aggregate flows every month. We compute flows for two Kemper funds. The first fund invests in large capitalization growth stocks and the second in large capitalization value stocks. For each of the two funds we aggregate flows into all share classes. There are six different share classes for the growth fund and four share classes for the value fund.

The second data set is retrieved from TrimTabs and includes aggregate (across all accounts) daily fund flows for three Oppenheimer mutual funds. Two funds are growth funds that invest in large capitalization stocks: Oppenheimer Enterprise and Oppenheimer Growth funds. The third fund invests in large capitalization value stocks: Oppenheimer Quest Value. We use daily fund flows from February 1998 through February 2001 to compute monthly flows.

IV. Risk Preferences of Growth and Value Investors

A. Do Investors in Value and Growth Indices Have Different Preferences Toward Risk?

The first hypothesis we test is whether investors in the two styles—value and growth—exhibit different preferences toward risk. For five value-growth index pairs we use prices of options on the indices to estimate the daily risk aversion (as a function of wealth) of the representative investor in the index. For each index we obtain a panel of estimates containing a time series of estimated risk aversion coefficients for each level of wealth.

Figure 1 is a plot of the estimated risk aversion as a function of expected future wealth for investors in the *Russell Midcap Growth* (*RDG*) and *Value* (*RMV*) indices. For each future wealth level in the range 0.96 through 1.00 we compute the average daily risk aversion estimates and the standard deviation.[15] The wealth level of 1.00 corresponds to the current wealth, and the wealth level of 0.98 corresponds to a 2% monthly (24% annual) loss. The plot shows the average value and the standard error band. Estimates for the value index are substantially higher than the estimates for the growth index. Over the period of study, investors in the value index are more averse to risk than the growth investors.

Figure 2 shows risk aversion as a function of wealth for investors in a different value-growth index pair: *Standard & Poor's Barra Growth (SGX)* and *Value (SVX)* indices. The figure covers the range of wealth levels from 0.98 through 1.02. The plot shows the average and the standard error band computed from daily risk aversion estimates for each level of wealth. For virtually all wealth levels risk aversion for the value index is substantially higher. Only in the small region that corresponds to losses (near $w = 0.98$) is the risk aversion for the growth index higher.

The results for the other three index pairs are shown in **Figure 3** through **Figure 5**. Risk aversion as a function of wealth for *Russell 1000 Growth (RLG)* and *Value (RLV)* indices is shown on **Figure 3**. Risk aversion for the value index, RLV, is higher for virtually all wealth levels. The only exception is a small region above $w = 1.005$ where growth investors are more averse to risk. **Figure 4** and **Figure 5** display the results for *Russell 2000 Growth (RUO)* and *Value (RUJ)* indices and for *Russell 3000 Growth (RAG)* and *Value (RAV)* indices, respectively. Investors in the value index have higher risk aversion than investors in the growth index for both index pairs. This holds for all wealth levels.

The figures suggest that value and growth investors have different preferences toward risk, and for the overwhelming majority of wealth levels, value investors display higher aversion to risk than the growth investors. Since for each wealth level we have a time series of estimates, we can conduct a formal statistical test for the difference in risk aversion. Table III shows the test results. Each panel in the table presents results for one pair of indices. For several wealth levels

[15] Wealth level is the future value of one plus the expected return.

the table shows the mean value of risk aversion for value index and for growth index. The table shows the results of the Satterthwaite difference in means test, which accounts for unequal variances, and the Brown-Mood non-parametric difference in medians test.

The tests reported in Table III, Panel A for the *Russell Midcap* Value-Growth index pair show that risk aversion for the value index is higher than that for the growth index for all wealth levels. The results hold for both the mean and the median. The results for *S&P Barra* Value-Growth index pair are reported in Panel B. The results support the conclusions from the **Figure 2**: Risk aversion for the value index is substantially higher for all wealth levels except for a small region in the neighborhood of $w = 0.98$, where risk aversion for the growth index is higher.

Table III, Panel C corresponds to **Figure 3** and reports the results for *Russell 1000 Growth (RLG)* and *Value (RLV)* indices. Value investors display higher risk aversion for all wealth levels except $w = 1.01$, and the statistical evidence for the difference is strong. Finally, panels D and E of the table confirm the results for *Russell 2000* and *Russell 3000* indices displayed in **Figure 4** and **Figure 5**: Risk aversion estimates for the value indices are higher at all wealth levels.

We conclude that over the periods of study investors in the value indices are more risk averse than investors in the growth indices.[16]

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[16] We perform numerous robustness checks and report two of the robustness checks in Appendix B. The robustness checks are based upon altering the procedure for computing risk aversion estimates. The results of the first robustness check are reported on Figure B1 and in Table B1. The true distribution under this alternation is now estimated using returns that are lagged by 6 months relative to the date when risk aversion is estimated. The results are virtually unchanged. The figures reported in the Appendix B are similar to **Figure 1** through **Figure 5**. The results in Table B1 are the same as those in Table III. As another robustness check (not reported) we modify the true distribution to investigate whether the shape of the tails affects the estimates. We determine that the procedure is robust to the shape of the tails – changing the tails does not affect risk aversion estimates. The results of the second robustness check are reported in Table B2. True distribution is estimated using returns on the Fama-French portfolio similar to the corresponding growth or value index. The full history of returns of the Fama-French portfolio is used, from 1926 until one month before the date when risk aversion is estimated. This is the case when investors form their assessment of the return distribution based on a long history of returns. The results are the same. Estimated risk aversion for the value index in a pair is higher than for the growth index. We also investigate the impact of the recent bubble period. We exclude the bubble period and use full history of returns for the period 1926 – 1996. The results (not reported for brevity) are unchanged.

Another pattern emerges from the examination of the figures and mean risk aversion values reported in Table III. There is apparent risk-seeking behavior, which is more pronounced in the case of investors in the growth indices. For *Russell Midcap* indices (**Figure 1**) risk aversion for growth index is below zero for all wealth levels, indicating risk seeking. Risk aversion is negative only for approximately 30% of the wealth interval for the value index in this pair. Mean values reported in Table III, Panel A confirm this.

Risk seeking is much less pronounced in the case of *S&P Barra* indices (**Figure 2**) than for any of the other index pairs. Negative risk aversion is present for the value index in approximately 3% of the wealth interval, and in approximately 29% of the interval for the growth investors (Table III, Panel B). Even in this case when both groups are largely displaying risk aversion we observe more regions of risk seeking for the growth index.

Growth investors exhibit risk seeking for all wealth levels for the remaining three index pairs (**Figure 3** through **Figure 5**). For *Russell 1000* indices there is also evidence of risk seeking for value investors. Approximately for 65% of wealth risk aversion estimates are below zero for the value index. For the *Russell 2000* pair risk aversion for the value index is positive for all levels of wealth. Finally, for *Russell 3000* risk seeking for the value index is present in approximately 50% of the interval. Overall, risk seeking has a stronger presence among growth indices.

Although risk-seeing behavior might appear unusual, there are a number of other asset-pricing studies that document it. We explore our results in relation to these previous findings in the "Discussion" section below. There is no previous evidence in the literature, however, showing that risk seeking is more of an attribute of a certain investment style and is more pronounced in the growth investment style than in value.

B. Time Series Evidence

For several indices in our sample, options are not available over a long period of time. This limits the time series of the estimated risk aversion. For example, for the Russell *Midcap Growth (RDG)* and *Value (RMV)* indices option data is available over the 13 months from December 2003 through December 2004. With only 13 monthly observations in the estimated risk aversion time series we do not perform time series tests using the data for these indices. More data is available for *S&P Barra Growth (SGX)* and *Value (SVX)* indices. For these indices we obtain monthly estimates of risk aversion for January 1996 through August 1998. For this pair of indices we study autocorrelation in the risk aversion time series.

Table IV, Panel A, reports autocorrelation in risk aversion for growth and value investors. autocorrelation for the growth index is positive at monthly horizons up to eight months (and is strongly significant for the horizon of up to five months). Autocorrelation becomes negative at the horizon of nine months, and is strongly statistically significant beginning with month ten. The pattern of short-term positive autocorrelation followed by negative autocorrelation is consistent with the existence of "return chasers."

Value investor risk aversion displays stronger persistence. Autocorrelation is higher in magnitude than in the case of growth investors and it is statistically significant at a longer horizon. Autocorrelation is positive and significant at the horizon of seven month and remains positive through month eleven. Autocorrelation becomes negative for the lag of twelve months.

Table IV Panel B and Panel C report results for *market-adjusted* risk aversion. Every month, we take the estimate of growth index risk aversion, $A_{G,t}$, and subtract the estimate of market risk aversion for that month, $A_{S\&P,t}$ This gives market-adjusted growth index risk aversion estimate,

$$X_{G,t} = A_{G,t} - A_{S\&P500,t}.$$

We use S&P 500 risk aversion for two wealth levels, w = 0.98 and w = 1.00, as a measure of market risk aversion. The same adjustment is performed for the value index to obtain market-adjusted value index risk aversion estimate,

$$X_{V,t} = A_{V,t} - A_{S\&P500,t}.$$

Panel C is the same as Panel B, except in Panel B we use S&P 500 and in Panel C we use S&P 100 as the measure of market risk aversion. For both panels we use growth (value) index estimate for wealth level w = 0.98.

B.1. Growth Investors

In Table IV, Panel B the first column shows autocorrelation in growth index investor risk aversion when S&P 500 risk aversion (w = 0.98) is used for the market adjustment. Risk aversion autocorrelation tends to be positive up to lag 7, and then turns negative from lag 7 through lag 12. First-order autocorrelation is positive, 0.45, and statistically significant with the *p*-value of 0.01. Autocorrelation is positive for lags 4, 5, and 6 and is statistically significant for lag 5 (autocorrelation coefficient equals 0.37 and *p*-value is 0.06). Autocorrelation becomes negative for lag 7, and is negative and significant for lags 11 and 12.

This pattern is even stronger when the S&P 500 risk aversion for w = 1.00 is used as a market adjustment (Table IV, Panel B, column 2). Autocorrelation is positive and statistically significant for the first four lags. It remains positive for lags 5 and 6 and turns negative at lag 7. Autocorrelation is negative and significant for lags 9 through 12.

The pattern in Table IV, Panel B, column 1 is (broadly) confirmed when we use S&P 100 as a market index (Table IV, Panel C, first column). Panel C, column 2 also (broadly) confirms the pattern in Panel B. The results are stronger when we use S&P 500 rather than S&P 100 risk aversion as the market adjustment.

B.2. Value Investors

The general pattern in autocorrelation in risk aversion for value index investors is different from the pattern for growth index investors. Autocorrelations for the value index are very persistent and tend to be positive for all lags. Table IV, Panel B, Column 5 shows autocorrelation for value index risk aversion when S&P 500 (w = 0.98) risk aversion is used for market adjustment. First order autocorrelation equals 0.88 and is highly significant. The pattern of positive and statistically significant autocorrelation persists for the first 8 lags. Autocorrelation remains positive for lags 9 through 12. This pattern is confirmed when S&P 500 (w = 1.00) is used as market risk aversion (column six of the table).

A similar pattern emerges when the risk aversion of S&P 100 investors is used as a market adjustment (Table IV, Panel C, columns 5 and 6). The value of autocorrelation is similar in magnitude. For lag 1, it equals 0.88 when the S&P 500 is used, and equals 0.81 when the S&P 100 index is the market proxy. For lag 4 these values are 0.74 and 9.68, respectively.

Our results to this point may be summarized as follows. For investors in the growth index autocorrelation in market-adjusted risk aversion exhibits the following pattern: It is positive for the first six month at monthly lags and becomes negative for the lags seven through twelve. One feature that characterizes autocorrelation in the risk aversion of value investors is persistence. The pattern in positive autocorrelation is stronger in the case of value investors than in the case of growth investors. At the same time, we do not observe negative autocorrelation at lags up to one year. This is consistent with investors in value funds being a more stable clientele, and with less "return chasing" on the part of the value investors. Apparently these are two features that we find to be associated with the "value" approach to investing. Time series results indicate that investors in the growth index exhibit a different pattern of behavior than investors in the value index. It appears that investors in the growth index show patterns consistent with "return chasing," while investors in the value index display more persistence.

C. Time Series Evidence of Switching

If there are investors that switch between the two investment styles, then there will be a contemporaneous negative correlation between changes in risk aversion. It will be induced by the switchers who leave one style and enter the other style, thus simultaneously impacting the risk aversion of investors in the two styles. Correlation between contemporaneous *change*s in risk aversion for SGX and SVG is negative, $corr\left(\Delta RA_{G,t}, \Delta RA_{V,t}\right) = -0.16$, where $\Delta RA_{i,t} = RA_{i,t} - RA_{i,t-1}$. Negative contemporaneous correlation in changes of risk aversion confirms the pattern in cross-autocorrelations for the levels of risk aversion.

D. Regressions: Changes in Preferences and Returns

If investors take past returns into account while allocating funds to different styles, then changes in risk aversion of a given style will be related to the past returns on that style and to the past returns on the competing investment style. To test this hypothesis we perform several regressions of the change in risk aversion on past returns.

Table V, Panel A shows regression results for changes in risk aversion in the growth index, S&P Barra Growth (SGX). The dependent variable is a change in risk aversion. The independent variables include lagged returns on the growth and value indices. The results indicate that relative past performance of growth and value styles is important in explaining changes in risk aversion of the representative investor in the growth style. The past returns on the growth and value indices are both statistically significant. The signs of the coefficients are consistent with the presence of investors who switch between styles based on relative past performance. A negative regression coefficient on the past growth return variable is consistent with a scenario where high past returns on the growth style attract switchers—who have relatively low risk aversion—and the inflow of switchers lowers the risk aversion of investors in the growth style. The regression coefficient on the value returns—which represent a style competing with growth—is positive. This also is consistent with the behavior of switchers. When value returns are high, switchers who have relatively low risk aversion leave the growth style (to switch to value) and the risk aversion in the growth index increases.

Table V, Panel B shows results for changes in risk aversion in the value index, S&P Barra Value (SVX). Only in one specification are the past growth and value returns statistically significant in explaining changes in risk aversion in the value index. This result is different from the result for changes in the growth index. Apart from the fact that relatively short time series present a challenge to our analysis, this finding is consistent with the behavior of growth and value investors. If the majority of investors in the value index are "value investors," then the representative investor will be less sensitive to past returns. At the same time, the signs of the coefficients are consistent with style switching. Negative regression coefficient on the past value return variable is consistent with the scenario when high past returns attract switchers. The regression coefficient on the growth returns—which represent a style competing with value—is positive. When growth returns are high, the switchers leave the value style and the risk aversion in the value index increases.

Generally, the switching hypothesis implies that high past returns on the style itself have a negative impact on risk aversion of the representative (the aggregate) investor in the index, because high returns attract switchers with a relatively low risk aversion. High past returns on a *competing* style have a positive impact on risk aversion, because switchers with a relatively low risk aversion leave for the competing style. The evidence in Table V is consistent with such behavior. It is also consistent with the view that there are differences in preferences among value and growth investors.[17]

[17] We also estimate the regressions using changes in *excess* risk aversion as the dependent variable. Excess risk aversion is defined as risk aversion in a growth or value style minus risk aversion of investor in the market, $ERA_{G/V,t} = RA_{G/V,t} - RA_{M,t}$. We use both S&P 500 and S&P 100 as proxies for the market. The change in excess risk aversion equals the change in risk aversion for the style minus the change in risk aversion for the overall market, $\Delta ERA_{G/V,t} = \Delta RA_{G/V,t} - \Delta RA_{M,t}$. The results are the same (not reported for brevity and available from the authors on request).

E. Regressions: Risk and Changes in Preferences

In addition to taking past returns into account when making decisions to invest in a style, investors may also take risk into account. Goetzmann and Massa (2002) study investors into S&P 500 Index mutual fund and their response to changes in volatility of the S&P 500. The results suggest that individual investor behavior may be conditioned upon risk. In Section II we discuss the implications of investor reaction to volatility with respect to risk aversion. We consider the case when there are two channels that impact risk aversion of the representative investor. First, there is the inflow of investors with relatively low aversion to risk, the "volatility chasers." Second, there may be another effect at work. Increased volatility could cause investors with high risk aversion to leave, causing a decline in risk aversion. The two channels are not mutually exclusive. We obtain three theoretical results. First, we show that *if the risk aversion of investors in a given style is equal (or nearly equal) to the risk aversion of volatility chasers (switchers), then there will be no change in the risk aversion of the representative investor in a style*. Second, when the risk aversion parameters of the switchers and investors in a style are *not* equal, then *an increase in volatility will lead to a decrease in risk aversion of the representative investor in a style*. Because value investors are more risk averse than the growth investors, we should expect a greater sensitivity to volatility in the case of value index. Our third result formalizes this intuition. When average risk aversion coefficients of volatility chasers, growth investors, and value investors are ranked as $a_S \leq a_G < a_V$, *the change in risk aversion of the representative investor in the growth index is smaller than the change in risk aversion of the representative investor in the value index.* In empirical tests, therefore, we expect stronger effect for the value index regressions.

To investigate its role, we include several measures of risk in the regressions. Table VI presents the results of the regressions of changes in the risk aversion for the growth index (Panel A) and the value index (Panel B). Two measures of risk are used. The first measure is the implied volatility of call options on the index. The second measure is realized volatility, measured as the annualized standard deviation of daily returns. For the growth index, risk is statistically significant at conventional levels only in one specification. If investors in the growth index have low risk aversion, then we may expect relatively low sensitivity to volatility. The negative sign of the coefficient, however, is consistent across specifications. This is consistent with our second hypothesis. The negative sign of the coefficient also suggests the presence of "volatility chasing," where higher volatility attracts investors with low risk aversion and leads to a decrease in risk aversion.[18] The results are unchanged when we use implied volatility from puts instead of calls, or when we use squared returns as the measure of risk. For example, the estimated regression equation with put implied volatility $IVP_{G,t-1}$, is

$$\Delta RA_{G,t} = \underset{(1.66)}{7.97} - \underset{(-2.32)}{95.1} \cdot R_{G,t-1} + \underset{(2.75)}{134.5} \cdot R_{V,t-1} - \underset{(-1.57)}{32.8} \cdot IVP_{G,t-1} - \underset{(-1.51)}{0.259} \cdot \Delta RA_{G,t-1},$$

where *t*-statistics are reported below coefficient estimates.

As predicted, the results are stronger for the value index (Panel B). We find that implied volatility is statistically significant in two specifications. Realized volatility is strongly significant in all specifications. Regression coefficients for volatility are negative in all specifications. An increase in risk leads to a decrease in risk aversion. This is consistent with the previously postulated hypothesis. The economic intuition behind this effect is that an increase in risk leads to inflow of investors with low risk aversion and thus to a decrease in risk aversion. This is consistent with "volatility chasing," where there are investors that enter an investment style when volatility of the style increases. The second channel may also be at work: Increased volatility could cause investors with high risk aversion to leave, causing a decline in risk aversion.

The regressions for growth and value indices are consistent with the presence of "volatility chasing" and show that risk plays a role in explaining changes in risk preferences of investors in growth and value styles.[19] A measure of risk based on past returns (standard deviation of past returns) performs much better in the regressions than a forward-looking measure of volatility (implied volatility). This is consistent with a scenario where "volatility chasers" use variability of past returns to form an assessment of risk. Overall, the results are consistent with the three hypotheses.

F. Regression Evidence of Style Switching

If there is a group of switchers who move funds between two styles, then changes in risk aversion in the growth and value indices will be related. Consider, for example, a case in which

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[18] Goetzmann and Massa (2002) report the presence of volatility chasers in their sample of mutual fund investors.

[19] We also observe that past returns of growth and value indices remain significant when a measure of risk is included in the regressions.

investors with a relatively high risk aversion leave one style and enter the other style. This will simultaneously cause a decline in a measure of risk aversion of investors in the first style and an increase in a measure of risk aversion of investors in the second style. We study the relationship between risk aversion of the representative investors in the growth and value indices by estimating the regression model,

$$RA_{V,t} = \underset{(0.18)}{0.98} + \underset{(7.54)}{0.83} \cdot RA_{V,t-1} - \underset{(-2.56)}{0.77} \cdot RA_{G,t} + \underset{(1.29)}{0.49} \cdot RA_{G,t-1} + \underset{(2.41)}{0.69} \cdot RA_{S\&P500,t} - \underset{(-2.59)}{0.73} \cdot RA_{S\&P500,t-1}$$

Lagged values are included to control for serial correlation. The regression confirms strong persistence in the risk aversion of the value fund clientele. Consistent with theoretical predictions, there is a negative relation between risk aversion of value fund investors and growth fund investors (coefficient equals -0.77 with *t*-statistic of -2.56). This is consistent with an investment strategy in which less risk-averse investors move funds between the two styles. The corresponding regression for the growth index is,

$$RA_{G,t} = \underset{(0.70)}{2.24} + \underset{(4.39)}{0.78} \cdot RA_{G,t-1} - \underset{(-2.56)}{0.28} \cdot RA_{V,t} + \underset{(2.85)}{0.30} \cdot RA_{V,t-1} + \underset{(3.89)}{0.59} \cdot RA_{S\&P500,t} - \underset{(-3.09)}{0.50} \cdot RA_{S\&P500,t-1}$$

For this regression, there is a negative relation between the risk aversion of growth and value investors. Comparing the two regressions, note that a change in growth risk aversion has a larger impact on the risk aversion of the investor in the value index (coefficient of -0.77) than a change in value risk aversion had on risk aversion in the growth index (coefficient of -0.28). This result, too, is consistent with the theoretical predictions.[20,21]

A change in excess risk aversion of investors in growth index has a larger impact on risk aversion of the representative investor in the value index (the coefficient is -0.25) than a change

[20] Note two other results. First, for both the value and growth regression, the coefficient for the contemporaneous market risk aversion is positive and significant (the values are 0.69 and 0.59, respectively). The risk aversion of both value and growth representative investors are positively related to the risk aversion of the representative investor in the market. Second, the regression results support the hypothesis of higher persistence of value investors, since coefficient on $RA_{V,t-1}$ in the first regression is larger in magnitude (and highly significant, *t*=7.54), while coefficient $RA_{G,t-1}$ in the second regression is smaller in magnitude (it is significant with *t*=3.89).

[21] The regression model is also estimated for *excess* risk aversion, which is defined as risk aversion in a growth or value style minus risk aversion of investor in S&P 500, $ERA_{G/V,t} = RA_{G/V,t} - RA_{S\&P500,t}$. The results are $ERA_{V,t} = \underset{(2.06)}{11.7} + \underset{(9.65)}{0.86} \cdot ERA_{V,t-1} - \underset{(-0.79)}{0.25} \cdot ERA_{G,t} - \underset{(-1.37)}{0.42} \cdot ERA_{G,t-1}$ and, for the excess value risk aversion, $ERA_{G,t} = \underset{(3.17)}{10.3} + \underset{(1.98)}{0.36} \cdot ERA_{G,t-1} - \underset{(-0.79)}{0.10} \cdot ERA_{V,t} + \underset{(0.87)}{0.10} \cdot ERA_{V,t-1}$. Again, we observe a stronger persistence in the case value investors than in the case of growth investors.

in risk aversion of the value investor has on risk aversion of the growth index representative investor (the coefficient is -0.10). The first coefficient is two-and-a-half times as large as the second. In the previous regressions with $RA_{V,t}$ and $RA_{G,t}$ as dependent variables we also observe this asymmetry (the corresponding coefficient values are -0.77 and -0.28; the first coefficient is 2-and-¾ times as large as the second).

The observed asymmetry is consistent with a well-known aggregation property. Suppose there are three types of investors: growth, value, and switchers each with a negative exponential utility function, identical wealth, and with coefficients of risk aversion $a_G = 0.7$, $a_V = 1.4$, and $a_S = 0.3$, respectively. In the case of negative exponential utility, risk aversion of the representative investor is the wealth-weighted harmonic mean of risk aversions of individual investors. Let there be 100 growth investors, 100 value investors, and 30 switchers in the economy. At the beginning the switchers are evenly distributed among the two styles. There are 100 growth investors and 15 switchers invested in the growth index. There are 100 value investors and 15 switchers invested in the value index. The risk aversion coefficients of the representative investor in the growth and value indices in this case are,

$$\frac{115}{a_{R,G}} = 100 \cdot \frac{1}{0.7} + 15 \cdot \frac{1}{0.3} \Rightarrow a_{R,G} = 0.5963$$

$$\frac{115}{a_{R,V}} = 100 \cdot \frac{1}{1.4} + 15 \cdot \frac{1}{0.3} \Rightarrow a_{R,V} = 0.9471$$

Next, consider a scenario where five switchers leave the value style and join the growth style. Since switchers have low risk aversion, this leads to a *decrease* in the risk aversion of the representative investor in the growth index, and an *increase* in risk aversion of the representative investor in the value index. This will have a larger impact on value than on growth index risk aversion. The new values are

$$\frac{120}{a^*_{R,G}} = 100 \cdot \frac{1}{0.7} + 20 \cdot \frac{1}{0.3} \Rightarrow a^*_{R,G} = 0.5727$$

$$\frac{110}{a^*_{R,V}} = 100 \cdot \frac{1}{1.4} + 10 \cdot \frac{1}{0.3} \Rightarrow a^*_{R,V} = 1.05$$

There is a 3.96% decrease in risk aversion for the growth index, and there is a 10.86% increase in risk aversion for the value index. The impact of the switching investors changing from value to growth is 2.75 as large for risk aversion on the value of risk aversion of the representative investor in the value index than in the growth index. This is the effect we observe in the data.

V. Evidence from Mutual Fund Flows

A. Time Series Evidence: The Autocorrelation Structure of Mutual Fund Flows

The purchase and sale of shares to mutual funds that are explicitly identified with a particular style is another way to examine the behavior of investors. Brown et. al. (2003) for example, found evidence that net flow into mutual fund styles in the U.S. and Japan captured a sentiment factor about the market, and that rotations of these factors effectively spread contemporaneous fund returns. In this section we use data on aggregate flows to value and growth mutual funds in the U. S. to study the contemporaneous and lagged response of investor flows in the Growth and Value styles. The data is from TrimTabs for the period from February 1999 through November 2006. It was provided to us as daily flows and we summed these to calculate monthly flows. The aggregate data covers flows to a representative selection of mutual funds in Growth and Value Morningstar categories.[22] We analyze monthly fund flows to Growth and Value fund categories in excess of the total fund flows.[23] That is, for each monthly flow number for each growth or value style, we subtract total flows across all categories for this month (this total is the total market flow).

Table VII, Panel A reports the autocorrelation in aggregate fund flows to growth and value mutual funds. The patterns in fund flow correlations are very similar to the patterns in autocorrelations in estimated risk preferences. For the growth fund flows, autocorrelation is positive at monthly horizons up to six months. This is the same horizon found for positive autocorrelation in estimated growth risk aversion in excess of the market reported in Panel B of Table IV. Autocorrelation becomes negative at the horizon of seven months, and is statistically significant beginning with month thirteen. The pattern of short-term positive autocorrelation followed by negative autocorrelation in the aggregate growth mutual fund flows matches the

[22] Trimtabs maintains a set of approximately 1,000 U.S. mutual funds from which they obtain daily NAV and NAV per share information that allows them to estimate daily net fund flows for this sample. In this sample are a number of Growth and Value funds, as classified by Morningstar. The number of grown and value funds in this set is not explicitly known to us.

[23] In their study of style investing Barberis and Shleifer (2003) argue that it is important to look for patterns in excess of the market. We also report, in the previous section and in Table IV, Panel B, results for risk aversion in excess of the market.

pattern in the growth index risk aversion. The change from negative to positive autocorrelation occurs in the same month for both time series.

The autocorrelation for the value fund flows is very similar to the value risk aversion autocorrelation pattern. Aggregate flows to value funds display a pattern of stronger persistence than aggregate flows to the growth funds. Autocorrelation is higher in magnitude than in the case of growth investors and it remains positive at a longer horizon. This pattern is the same in the time series of estimated value risk aversion.

To study the behavior of investors we also use data on flows at the level of individual mutual funds. Our data set includes a panel of individual mutual fund accounts for Kemper mutual funds for five years, 1995 through 1999. We use the individual account data to compute aggregate flows every month for Kemper large capitalization growth fund, and Kemper large capitalization value fund. We also use aggregate (across all accounts) daily fund flows for three Oppenheimer mutual funds: two large capitalization growth funds, and one large capitalization value fund. We use daily fund flows from February 1998 through February 2001 to compute monthly flows. The particular advantage of the Kemper dataset is that the disaggregate account-level information allows us to identify fund clienteles.

Table VII, Panel B reports the autocorrelation in fund flows for Kemper growth and value funds. The patterns in fund flow correlations are similar to the patterns in autocorrelations in estimated risk preferences. For the growth fund flows, autocorrelation is positive at monthly horizons up to seven months (and is statistically significant for the horizon of up to six months). Autocorrelation becomes negative at the horizon of eight months, and is statistically significant beginning with month twelve. The pattern of short-term positive autocorrelation followed by negative autocorrelation in the growth mutual fund flows matches the pattern in the growth index risk aversion. The change from negative to positive autocorrelation occurs in approximately the same month for both time series.

The autocorrelation pattern of the fund flows for the value funds is similar to the value index risk aversion autocorrelation pattern. Flows to the individual value funds display a pattern of stronger persistence than flows to the growth funds. Autocorrelation is higher in magnitude than in the case of growth investors and it remains positive at a longer horizon. Autocorrelation is positive and significant at the horizon of six month and remains positive through month eighteen.

Panel C contains results for the Oppenheimer funds—two growth funds and a value fund. Patterns in autocorrelations are the same as in the case of Kemper funds. Also, there is significant contemporaneous negative correlation between flows to the growth and value funds. Correlation between flows to the first growth fund and the value fund is -0.30 (*p*-value is 0.01); correlation between flows to the second growth fund and the value fund is -0.24 (*p*-value is 0.04).

Fund flow results provide some direct evidence on behavior. Overall, patterns in mutual fund flows at the aggregate and disaggregate level show short-term monthly persistence and longer term reversion. The value fund flows appear to show longer positive persistence than the Growth fund flows, in general. During the time period of study, these flow patterns are similar to the patterns in estimated risk preferences. As such they are consistent with the existence of clientele shifts as the cause of risk aversion changes.

B. Flows to Growth and Value Mutual Funds Conditional on Risk, and Return

In this section we use the excess monthly flows to growth and value funds from TrimTabs to study patterns in investor behavior conditional on risk and return. The results for changes in risk aversion indicate that the changes for growth investors are sensitive to past returns on both growth and value styles, and are not sensitive to risks (Table V, Panel A and Table VI, Panel A). The results from regressions of changes in risk aversion in the growth index on lagged risks and returns are consistent with the presence of switchers who follow returns. To study the response of growth fund flows to risks and returns, we perform regressions of flows in the growth style on the lagged risks and returns of the growth style, and on those of the competing style, value. The results for growth fund flows are reported in Table VIII, Panel A. The dependent variable is the flow to growth funds in month t. The independent variables include lagged return on the growth/value funds computed for month $t-1$ as the average of daily returns within a month, $RET_{G/V,t-1}$. We use two measures of risk: $S_{G/V,t}$ is the standard deviation of daily returns on the growth/value style in a given month, t; and $r^2_{G/V,t}$ is the average of squared daily returns in a given month.

One estimated regression for the excess flows to the growth funds is reproduced below,

$$XFL_{G,t} = \underset{(1.58)}{144.8} + \underset{(4.55)^{***}}{0.450} \cdot XFL_{G,t-1} + \underset{(2.12)^{**}}{65297} \cdot RET_{G,t-1} + \underset{(1.93)^{*}}{61363} \cdot RET_{G,t-2}$$
$$- \underset{(-3.13)^{***}}{166036} \cdot RET_{V,t-1} + \underset{(0.13)}{7073} \cdot RET_{V,t-2}$$
$$R^2_{Adj} = 0.353, \quad DW = 2.14.$$

The *t*-statistics are reported in parentheses below coefficient estimates. The coefficient on lagged return on the growth style is positive (and significant at 5%). The flow to the growth funds increases with past returns on the growth funds. The coefficient on lagged return on the alternative style, value, is negative (and significant at 1% level). The flow to the growth funds decreases when past returns on the alternative—the value style—are high. The results for other regression specifications are reported in Table VIII. We find that growth flows are not sensitive to risks. We also find that flows to the growth funds are sensitive to returns. Flows increase with returns on growth (there is a positive relation), and flows to growth decrease with returns on value (there is a negative relation). These results are consistent with the presence of switchers who follow returns. The pattern in growth fund flows is also consistent with the pattern for estimated risk aversion coefficients for the growth style.

The results for changes in risk aversion indicate that changes for value investors behave differently than for growth. For value investors, changes in risk aversion are sensitive to risks (Table VI, Panel B). To investigate whether a similar pattern hold in fund flows, we regress flows to value on past risk and returns. The results are reported in Table VIII, Panel B. One estimated regression for the excess flow to the value funds is reproduced below,

$$XFL_{V,t} = \underset{(2.53)^{***}}{834.4} + \underset{(6.53)^{***}}{0.670} \cdot XFL_{V,t-1} - \underset{(-1.59)}{57200} \cdot RET_{G,t-1} + \underset{(0.55)}{18059} \cdot RET_{G,t-2} + \underset{(0.20)}{10884} \cdot RET_{V,t-1}$$
$$+ \underset{(0.51)}{26665} \cdot RET_{V,t-2} - \underset{(-2.67)^{***}}{56451} \cdot S_{G,t-1} + \underset{(1.47)}{30920} \cdot S_{G,t-2} - \underset{(-2.07)^{**}}{46609} \cdot S_{V,t-1} + \underset{(0.94)}{20382} \cdot S_{V,t-2}$$
$$R^2_{Adj} = 0.542, \quad DW = 2.27.$$

The *t*-statistics are reported in parentheses below coefficient estimates. The regression suggests that flows to value funds display higher persistence than flows to the growth funds. The results also suggest that past returns on the two alternative styles have a smaller impact on flows to the value funds than they have on flows to the growth funds. The regression coefficients for lagged measures of risk $S_{G,t-1}$ and $S_{V,t-1}$ are negative and statistically significant. This suggests that flows to value funds are sensitive to risks. The negative signs are consistent with risk aversion of value investors—an increase in risk results in lower flow to the value funds. The results for other regression specifications are reported in Table VIII. Overall, the results for value fund flows are similar to the results reported in Tables V and VI for the risk aversion coefficient.

Comparing regression results for flows to growth funds to the results for value funds, we find that regression coefficients for measures of risk are larger in the value regressions than in the growth regressions. The coefficients for risk measures are significant in the value regressions and are generally not significant in the growth regressions. Flows to value funds are more sensitive to risk than flows to growth funds. This pattern is consistent with the value investors being more risk averse than growth investors.

Next, we investigate whether there is evidence of switching behavior in the fund flows. Following Goetzmann et. al. (2000) and Brown et. al. (2003) we perform principal component analysis on excess flows to the style categories. Two factors (principal components) are extracted. The second factor is such that the excess flows to growth and value funds load with opposite signs. Excess flow to growth has a positive loading on this factor, while excess flow to value has a negative loading on this factor. We refer to this factor as switching factor, PC_S . We find that excess flows to both growth and value funds have a positive loading on the second factor. To assist in the interpretation of the first factor as the switching factor, we regress this principal component on the risks/returns of growth and value funds. Table VIII, Panel C contains regression results. One estimated regression is reproduced below:

$$PC_{S,t} = \underset{(-0.15)}{-0.007} + \underset{(12.70)^{***}}{0.778} \cdot PC_{S,t-1} + \underset{(2.64)^{***}}{42.26} \cdot RET_{G,t-1} + \underset{(0.59)}{9.51} \cdot RET_{G,t-2} - \underset{(-3.02)^{***}}{78.82} \cdot RET_{V,t-1} - \underset{(-0.01)}{0.26} \cdot RET_{V,t-2}$$

$$R^2_{Adj} = 0.674, \quad DW = 2.30.$$

The *t*-statistics are reported in parentheses below coefficient estimates. The coefficient estimate for return on the growth style is positive and significant at 1% level. The factor responds positively to an increase in lagged returns on the growth style at the monthly horizon. The coefficient estimate for return on the value style is negative and significant at 1% level as well. The factor decreases in response to an increase in lagged return on the value style. The signs of both coefficients are consistent with the interpretation that this factor is the factor that captures switching behavior from value to growth.[24] The results for other regression specifications are reported in Table VIII, Panel C. When the switching factor is regressed on risk and returns we

[24] We also perform this test using raw flows to growth and value funds (not excess flows) to extract two principal components. The results are unchanged. We find that there is one factor that excess flows to growth and value funds load on with opposite sign. When this factor is regressed on lagged growth and value returns, the results are the same.

find that the coefficients on returns remain significant. We also find that the switching factor is not sensitive to risks—a finding consistent with the hypothesis that switchers have very low risk aversion. Overall, the results suggest that the patterns in growth and value fund flows are also consistent with the patterns for estimated risk aversion coefficients for the growth and value styles. This result sheds some light on the Goetzmann at al. (2000) and the Brown et. al. (2003) results. The natural interpretation of fund flow factors is as a sentiment variable. The proposed model and tests on fund flows suggests that that sentiment might be explained more fundamentally in terms of clienteles differentiated by risk aversion and return-chasing behavior.

VI. The Performance of Trading Strategies

The results thus far suggest that style clienteles may differ significantly in the dimension of risk aversion. Our analysis suggests that investors in the value index (and its derivative securities) have a higher aversion to risk, than investors in the growth index (and its derivative securities). In this section we investigate whether it is possible to construct a trading strategy to exploit these differences in risk preferences, to, if effect, buy risk in one market and sell it in the other.

Table IX reports the results of several option trading strategies. For all strategies we use options on the growth and value index pairs. A portfolio with zero initial investment is formed every month by selling option contracts on the growth index and investing the proceeds in options on the corresponding value index. Our method for calculating option returns follows Coval and Shumway (2001). We take options that are to expire during the following calendar month, and therefore are roughly between 29 and 37 days to expiration. Similarly to Coval and Shumway (2001), we take the midpoint of the bid-ask spread and use this to calculate payoffs for our trading strategies. For each value-growth index pair, we sell a portfolio of options on the growth index and use the proceeds to buy a portfolio of options on the corresponding value index. The portfolio is held until maturity, at which time the payoffs are realized. A new portfolio is formed.

The first trading strategy involves selling two call options on the growth index with strike prices nearest to the current index level, one strike above and one strike below it. The proceeds from the sale are invested in two call options on the corresponding value index with strike prices nearest to the index value. The first column in Table IX refers to a *portfolio* strategy. The column contains results for an equal-weighted portfolio of four value-growth index pairs for which data is available for the same time period.[25]

The second trading strategy consists of trading straddles on value and growth indices. To determine whether put and call options earn different rates of return when priced by value and growth investors, we direct our attention toward the returns of straddle positions. By forming straddle positions by combining puts and calls with the same strike price and maturity, we can focus on the pricing of higher moments of security returns. As before, we take options that are to expire during the following calendar month. A straddle consists of a call and a put option with the same strike price, chosen as the strike closest to the current value of the underlying index. We sell a straddle on the growth index, and invest the proceeds in a straddle on the corresponding value index. Similarly to the first strategy, this strategy requires zero initial investment.

Straddles allow us to focus on the pricing of risk because, while straddles are not sensitive to the returns on the underlying asset (the deltas of our at-the-money short-term straddles are near zero), they are sensitive to the volatility of the underlying. When volatility is higher than expected, a long straddle position has positive returns. Straddles have a large, positive, exposure to volatility risk. This makes trading strategies involving straddles ideal for studying the effects of volatility pricing. We now examine the performance of these two investment strategies.

Table IX records a variety of statistics for the two trading strategies for five index pairs and for the portfolio strategy. We record the ending dollar value of the strategy,[26] the mean monthly payoff, standard deviation of payoffs, minimum and maximum monthly payoffs. The *t*-statistic associated with a null hypothesis of zero mean payoff is recorded in the fourth row.

For the first strategy, where we trade call options, the payoffs are positive for all five pairs and for the portfolio strategy. A zero-investment trading strategy tends to earn an average payoff of between 4.17 dollars and 7.99 dollars per month. The return is statistically significant

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[25] These four pairs are (1) Russell Midcap Growth (RDG) and Value (RMV), (2) Russell 1000 Growth (RLG) and Value (RLV), (3) Russell 2000 Growth (RUO) and Value (RUJ), and (4) Russell 3000 Growth (RAG) and Value (RAV).

[26] All strategies require zero initial investment.

for the portfolio of four pairs and for two index pairs, with *t*-statistic above 2.16. For the remaining three index pairs we obtain *t*-statistics of 1.65, 1.61, and 1.53 – marginal and not significant at traditional confidence levels. Monthly profits and losses for the strategy a plotted in Figure 6A.

It may be useful to compare our results, and the statistical significance we obtain, to the numbers reported by other researchers who have studied returns on index options. Coval and Shumway (2001) study returns of call, put, and straddle positions for options on two market indices, S&P 500 (SPX) and S&P 100 (OEX). They find that S&P500 call options tend to earn positive returns in excess of those on the underlying index. An at-the-money call option tends to earn an average return of between 1.85 percent and 2.00 percent per week. Although high in magnitude, these returns, however, are not statistically significant because of high variance (Table I of their paper). S&P 100 call option returns in their sample exhibit similar characteristics. Here, the *t*-statistic reported for the call options below and above the current index value are 1.61 and 1.55. These numbers are comparable to the *t*-statistic we obtain for call option trading strategies for three index pairs.

In Table IX we report the performance of the second strategy that entails trading straddles on each index in a value-growth index pair. As before, we record the ending dollar value of the strategy, the mean monthly payoff, standard deviation of payoffs, minimum and maximum monthly payoffs. The *t*-statistic associated with a null hypothesis of zero mean payoff is recorded in the fourth row. Average monthly payoffs are positive for all five pairs and for the portfolio, ranging from 2.15 dollars to 7.02 dollars. Positive payoffs are highly statistically significant for the portfolio of four index pairs (*t*-statistic of 3.17) and for three out of five index pairs (*t*-statistic of 2.13, 3.88, and 3.08). For the remaining two index pairs the values of *t*-statistic are 1.75 and 1.20. Figure 6B is a plot of monthly profits and losses for the strategy.

Overall, the evidence suggests that investment strategies based on trading options on value and growth indices are profitable, however the scale and significance depends upon the ability to trade within the spread. This holds for the strategy that involves trading call options and for the strategy based on trading straddles.

VII. Discussion

A. Convexity of Preferences: Empirical Findings

The first notable finding in this paper is a simple, but striking one: the existence of negative risk aversion estimates for investors in growth funds (and derivatives) over the period of study. We are not the only authors who report negative estimates for risk aversion. Negative risk aversion, or evidence of risk-seeking, has been reported in several studies that we review in this section. Jackwerth (2000) uses S&P 500 Index options and index returns to estimate risk aversion as a function of wealth. He reports that using the data after 1987 crash, there is evidence of negative risk aversion. He uses many robustness checks and finds that these results do not change. Rosenberg and Engle (2002) use S&P 500 index option prices and estimated S&P 500 return densities to estimate the empirical pricing kernel and empirical risk aversion each month from 1991 to 1995. Pricing kernels are estimated using several specifications: a *power pricing kernel*, and an *orthogonal polynomial pricing kernel*. The reported pricing kernels have a region of *increasing marginal utility*. The authors report that estimates of the orthogonal polynomial pricing kernel exhibit risk-aversion characteristics similar to those in Jackwerth (2000). The authors find that there is a region of *negative absolute risk aversion* over the range from -4% to 2% (monthly returns) and that absolute risk aversion increases for returns greater than -4%. The shape of estimated average absolute risk aversion function reported in Rosenberg and Engle (2002) is similar to Jackwerth's estimate over a similar time period.

Kliger and Levy (2002) study risk preferences using S&P 500 index options from December 1987 through December 1995, using monthly observations of option prices (they report using option prices for 74 months in the sample period). Using estimation methods similar to those in Jackwerth (2000), they, too, report that risk aversion estimates become "negative at a (monthly) rate of return of about 3%, suggesting plausibility of models in which preferences exhibit risk seeking behavior."

In a recent study Bakshi and Wu (2006) use options on Nasdaq 100 index to study the price of risk during recent Internet bubble. They report finding *positive* market price of risk in 1999, which is consistent with risk loving behavior. Evidence of negative risk aversion has also been reported in studies that do not directly extract asset return distributions from option prices. In their study of option returns, Coval and Shumway (2001) use the generalized method of moments (GMM) to estimate parameters of the pricing kernel using S&P 500 straddle returns. They report negative estimates of the risk aversion parameter.

Studies that do not use options market data also report evidence of risk seeking behavior in a variety of settings. Post and Levy (2005) use stochastic dominance criteria that take into account (local) risk seeking and analyze the efficiency of the market portfolio relative to several benchmark portfolios. Their results suggest that reverse S-shaped utility functions with risk aversion for losses and risk seeking for gains—such as those proposed by Markowitz (1952)—can help explain stock returns. The authors write: "Our results suggest that *no* concave utility function can rationalize the market portfolio. Under our maintained assumptions, this implies that investors who hold the market portfolio (for example, index funds or exchange traded funds) are not globally risk averse and utility is not everywhere concave, and we have to account for (local) risk-seeking behavior." The authors postulate that "reverse S-shaped utility functions best capture investor preferences, and that risk aversion over losses and risk seeking over gains helps explain the cross-sectional pattern of stock returns."

Whereas Post and Levy (2005) base their conclusions on the behavior of prices, in another study Coval and Shumway (2005) study behavior of Chicago Board of Trade traders. The study finds that proprietary traders are highly loss-averse and regularly take on high risk to recover from prior losses. These risk-seeking trades impact prices in the short run.

A few researchers have studied prices of lottery bonds—securities that have payoffs similar to those of lottery tickets. A careful reading of these papers reveals evidence of risk seeking behavior. Green and Rydqvist (1997) use Swedish government lottery bonds to study pricing of idiosyncratic risk and find that despite its idiosyncratic nature, prices appear to reflect aversion to this risk. For one of the bonds in the sample, however, the authors report a *premium paid* for holding diversifiable risk. When analyzing price behavior of Swedish lottery bonds, Green and Rydqvist (1997) postulate that violations of concavity of the investors' utility function may be in evidence in their sample. They also report evidence that there are cases when the marginal investor values the lottery risk. Given the pricing in the Swedish lottery bond market, the authors conclude that "it is possible that investors are averse to the lottery risk associated with the smaller payoff levels, yet still value the chance at very high payoffs."

Florentsen and Rydqvist (2002) study Danish lottery bonds which are Danish Treasury obligations and make coupon payments by lottery. Most bonds receive no payments, while a few winning bonds receive prizes up to 10,000 times the face value.[27] A close look at Danish lottery bond prices reported in the paper reveals a pattern consistent with risk-seeking behavior. Florentsen and Rydqvist (2002) present a plot of the current yield for lottery bonds from 1976 to 1999 and compare it to the yield on regular Treasury bonds (Figure 3 in their paper). The plot shows that lottery bond yields are substantially *lower* than regular Treasury yields, most of the time. The difference is significant, often above five percentage points and frequently reaching six percentage points. For example, in the late 1980s the yield on lottery bonds was approximately 3%, while the Treasury yield stood at 9%. They also report that lottery bonds were selling at an average price of 250% of par. Another plot in the paper shows the time-series of the yield to maturity for bonds issued in 1977 (Figure 4 in their paper). From it, one can see that a 1977 bond traded at *negative* yields to maturity during the time period 1998—1999. Florentsen and Rydqvist (2002) point out that the model developed by Green and Rydqvist (1999) to explain negative yields to maturity in the Swedish lottery bond market based on tax arbitrage does not apply to the Danish market because the marginal tax rate is zero. Florentsen and Rydqvist (2002) therefore call negative yields to maturity in the Danish lottery bond market "a puzzle which we leave for future research." Behavior of Danish lottery bond prices is consistent with investors exhibiting preference toward the lottery and bidding up the prices until the bonds have negative yields to maturity.

In the context of this previous research documenting negative risk aversion, our findings are not as surprising as one might initially think. Risk-seeking behavior evidently appears in other financial market contexts. What thus notable in the current study is that we have found that it characterizes the risk attitude of the representative investor of one major investment style in a particular period in U.S. capital market history. On the other hand, for investors in the value style we typically find evidence of risk aversion. Is negative risk-aversion irrational – even irrationally exuberant? That is a natural question to ask, but certainly beyond the scope and empirical basis of this paper.

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[27] Their study is focused on the behavior of ex-day returns. Consistent with the costly arbitrage model of Kalay (1982) and Boyd and Jagannathan (1994), they find that the marginal valuation of the dividend is one-for-one, but that prices on average fall by more than the amount of the dividend. They conclude that abnormal ex-day returns reflect the cost of arbitrage.

B. Convexity of Preferences: Theoretical Literature

Concave utility functions that are extensively used in finance correspond to economic intuition and have convenient mathematical properties. Concave functions, however, cannot explain gambling and strong evidence that economic agents willingly participate in activities with negative expected returns. This motivated one of the first modifications to the concave utility function.

To explain the coexistence of gambling and insurance in human behavior Friedman and Savage (1948) propose that an individual's utility of wealth function is composed of two (strictly) concave segments separated by a (strictly) convex segment. Markowitz (1952) argues that the Friedman and Savage utility function should be modified so that the inflection point where the concave region turns into convex region is located exactly as the current wealth level. Thus, Markowitz (1952) proposes a utility function with a reference point.

The notion of increasing marginal utility (convexity) causes certain discomfort among the economists. Kwang (1965) suggested a resolution of the problem that is based on the indivisibility of consumption. Kwang (1965) showed that gambling can be consistent with the principles of utility maximization when indivisibility of consumption is introduced. Individuals purchase lottery tickets with payoffs that give them a positive probability of moving to a new consumption level by being able to afford an indivisible consumption good. If the cost of purchasing a car, a house, a university education, or a business, appears far beyond the existing means, it becomes rational for an individual agent to participate in a gambling opportunity that offers a chance of a sufficiently high payoff. Winning such a lottery would bring the individual to a qualitatively new "level" of consumption.

Another paper offers a very attractive explanation for the existence of convex regions in the individual's utility function. Hakansson (1970) starts with the observation that since money is only a means to an end (consumption), the derived utility of wealth is dependent on the utility of consumption and the opportunities for achieving it. Mathematically, the derived utility of wealth function is defined as

$$J[W(t),t] \equiv Max\, E_t\left[\sum_{s=t}^{T-1} U(C,s) + B(W_T,T)\right],$$

$$J[W(T),T] \equiv B(W_T,T).$$

In this case the terminal date T is assumed known and the utility function is assumed additively separable. In this formulation $U(\bullet)$ is the utility of consumption and $B(\bullet)$ is the utility of bequest. Clearly, the utility of present wealth is influenced by preferences over consumption at each future point in time, utility over bequest, the agent's labor income, future interest rates, the risk and return of the future investment opportunities, and borrowing restrictions. Therefore, the determination of an individual's utility of current wealth requires a model of his total economic decision problem, including the description of the investment opportunity set and restrictions, such as borrowing or short-sale constraints. Hakansson (1970) develops such a model. He begins with risk averse preferences over consumption. He then imposes a borrowing constraint of a reasonable form and finds that the constraint gives rise to a Friedman-Savage utility function of current wealth.

Perhaps the most well-known class of value functions is the prospect theory *S*-shaped function suggested by Kahneman and Tversky. Based on their experimental results, Kahneman and Tversky (1979) and Tversky and Kahneman (1992) suggest that the value function is convex in the domain of losses (below the current wealth level) and concave in the domain of gains (above the current wealth). This function has one inflection point located at the current level of wealth.

Does convexity create havoc with our asset pricing theories that usually start with the assumption of concave utility? Not necessarily. Jarrow (1988) studies an economy consisting of an infinite number of assets and shows that the Arbitrage Pricing Theory does not require that agents possess preferences that can be represented by risk-averse expected utility functions. This suggests that risk seeking *per se* does not conflict with the APT.

Blackburn and Ukhov (2005) show that risk-seeking behavior at the individual level can be consistent with risk-averse behavior at the aggregate level. The authors begin with a model where all agents have a convex utility implying they are risk seekers. The agents face a constraint—they cannot infinitely borrow (or sell short). When agents are heterogeneous with respect to the initial endowment, under perfect competition the economy is risk averse.

VIII. Conclusion

We use option prices on five value and five growth indices to examine preferences toward risk of investors in value and growth indices, two popular investment styles. The selected five value-growth index pairs are widely followed by investors and are frequently used as benchmarks for the growth and value investment styles. We adopt a flexible approach and use a methodology for estimating risk aversion coefficient that does not assume a specific form for the utility function. We find several effects. First, our findings suggest that different investor clienteles exist. Second, we identify *risk preferences* as an important attribute that categorizes differences across the two clienteles. We find differences in preferences toward risk for investors in these two styles. Value investors are more risk averse than are the growth investors. The difference in preferences toward risk is present for all value-growth index pairs.

Third, we find that not only risk preferences of value and growth investors are different in *levels*, but also that they have differences in time series patterns. Risk preferences of value investors exhibit a stronger persistence in the time series. This is consistent with the hypothesis of a more stable clientele of investors who invest in the value index. Investors in growth indices display less persistence. This is another attribute that categorizes the two clienteles. When we study flows in value and growth mutual funds, we find that the time series patterns in flows match the patterns in risk preferences.

Fourth, we show that estimated risk preferences are consistent with the presence of “style switchers” who switch between value and growth styles. Investors in value and growth styles react to past returns, as well as to the risk of the two styles. The existence of investors who switch between styles has implications not only for asset returns, but also for characteristics of the representative investor in the two styles. Our evidence on the time series behavior of risk preferences of value and growth index investors is consistent with the presence of style switching behavior. This finding is also supported by the funds flow data, both at the aggregate level and at the level of flows to individual mutual funds.

Fifth, we construct trading strategies in value and growth index options markets. We show that trading with the two clienteles—by selling options on the growth index and investing in options on the value indices—generate positive returns. Taken together, the evidence is consistent with the existence of investor clienteles with differential attitudes toward risk.

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Appendix A

Proof (Reaction to volatility). The assumption is maintained that $a_S \le a_G < a_V$. The objective is to show that the change in risk aversion of the representative investor in the growth index is smaller than the change in risk aversion of the representative investor in the value index, in absolute value, $da_{R,G} < da_{R,V}$. Using the expression for the change, we need to show:

$$\left| \frac{a_G \cdot a_S \cdot (a_G - a_S)}{(a_S n_G + a_G n_{S,G})^2} \left[n_{S,G} \cdot dn_G - n_G \cdot dn_{S,G} \right] \right| < \left| \frac{a_V \cdot a_S \cdot (a_V - a_S)}{(a_S n_V + a_V n_{S,V})^2} \left[n_{S,V} \cdot dn_V - n_V \cdot dn_{S,V} \right] \right|. \quad \text{(A1)}$$

We maintain the assumptions that the two styles are equal in size, $x \equiv n_G = n_V$; there is an equal number of "volatility chasers" originally invested in the two styles, $y \equiv n_{S,G} = n_{S,V}$; when volatility increases, the changes in the numbers of investors in the two styles will be equal, too: $dn_G = dn_V$, and $dn_{S,G} = dn_{S,V}$ (we analyze relative impact on risk aversion of representative agent in a style, holding *all else* equal). Then (A1) becomes,

$$\frac{a_G \cdot a_S \cdot (a_G - a_S)}{(a_S n_G + a_G n_{S,G})^2} < \frac{a_V \cdot a_S \cdot (a_V - a_S)}{(a_S n_V + a_V n_{S,V})^2} \Leftrightarrow \frac{a_G \cdot (a_G - a_S)}{(a_S x + a_G y)^2} < \frac{a_V \cdot (a_V - a_S)}{(a_S x + a_V y)^2} \quad \text{(A2)}$$

$$a_G \cdot (a_G - a_S)(a_S x + a_V y)^2 < a_V \cdot (a_V - a_S)(a_S x + a_G y)^2$$

Let $G \equiv a_G \cdot (a_G - a_S)$, $V = a_V \cdot (a_V - a_S)$. Simplifying, obtain

$$G \cdot a_S^2 x^2 + a_G a_S a_V \left[2a_G xy - a_V y^2 \right] < V \cdot a_S^2 x^2 + a_G a_S a_V \left[2a_V xy - a_G y^2 \right] \quad \text{(A3)}$$

Since $G < V$, the sufficient condition for (A3) to hold, and for the main result to obtain, is that

$$a_G a_S a_V \left[2a_G xy - a_V y^2 \right] \le a_G a_S a_V \left[2a_V xy - a_G y^2 \right]$$

The above always holds for $y = 0$. Hence, assume $y \ne 0$ and simplify, obtaining,

$$2a_G x - a_V y \le 2a_V x - a_G y.$$

Rearranging,

$$2a_G x + a_G y \le 2a_V x + a_V y \Leftrightarrow a_G (2x + y) \le a_V (2x + y).$$

The last inequality holds because $a_G < a_V$. *Q.E.D.*

Proof (Asymmetric impact on growth and value). The assumption is maintained that $a_S \le a_G < a_V$. Style switchers leave one style and enter the other, $dn_{S,G} = -dn_{S,V}$, and $dn_G = dn_V = 0$ so that the switchers are the ones driving the changes. The objective is to show that the change in risk aversion of the representative investor in the growth index is smaller in magnitude (in absolute value) than the change in risk aversion of the representative investor in the value index, $|da_{R,G}| < |da_{R,V}|$.

To show this, observe that (A2) holds when $dn_{S,G} = -dn_{S,V}$, and $dn_G = dn_V = 0$. The arguments above apply. *Q.E.D.*

Table I
Description of Growth and Value Indices Used in the Study

Index	Ticker	Data Range
Russell Midcap Growth Index RDG Index measures the performance of those Russell Midcap companies with higher price-to-book ratios and higher forecasted growth values.	RDG	December 2003 – December 2004
Russell Midcap Value Index RMV Index measures the performance of those Russell Midcap companies with lower price-to-book ratios and lower forecasted growth values.	RMV	December 2003 – December 2004
The Standard & Poor's Barra Growth Index SGX Index is a capitalization-weighted index of all the stocks in the Standard & Poor's 500 that have high price-to-book ratios. The index was developed with a base value of 35 as of December 31, 1974. The index is rebalanced semi-annually on January 1 and July 1. It is designed so that approximately 50% of the SPX market capitalization is in the Growth Index.	SGX	January 1996 – December 1998
The Standard & Poor's Barra Value Index SVX Index is a capitalization-weighted index of all the stocks in the Standard & Poor's 500 that have low price-to-book ratios. The index was developed with a base value of 35 as of December 31, 1974. The index is rebalanced semi-annually on January 1 and July 1. It is designed so that approximately 50% of the SPX market capitalization is in the Value Index.	SVX	January 1996 – December 1998
Russell 1000 Growth Index RLG Index measures the performance of those Russell 1000 companies with higher price-to-book ratios and higher forecasted growth values. The index was developed with a base value of 200 as of August 31, 1992.	RLG	November 2003 – December 2004
Russell 1000 Value Index RLV measures the performance of those Russell 1000 companies with lower price-to-book ratios and lower forecasted growth values. The index was developed with a base value of 200 as of August 31, 1992.	RLV	November 2003 – December 2004
Russell 2000 Growth Index RUO Index measures the performance of those Russell 2000 companies with higher price-to-book ratios and higher forecasted growth values.	RUO	December 2003 – July 2005
Russell 2000 Value Index RUJ Index measures the performance of those Russell 2000 companies with lower price-to-book ratios and lower forecasted growth values.	RUJ	December 2003 – July 2005
Russell 3000 Growth Index RAG Index measures the performance of those Russell 3000 Index companies with higher price-to-book ratios and higher forecasted growth values.	RAG	December 2003 – July 2005
Russell 3000 Value Index RAV Index measures the performance of those Russell 3000 Index companies with lower price-to-book ratios and lower forecasted growth values.	RAV	December 2003 – July 2005

Table II
Performance Summary Statistic

Average Return is annualized average monthly return for the period; *Standard Deviation* is annualized standard deviation of monthly returns; *Sharpe Ratio* is the ratio of excess return on the portfolio to the portfolio standard deviation,

$$S_p = \frac{r_p - r_f}{\sigma_p}.$$

The risk-free rate is the average monthly Treasury Bill rate over the corresponding period. The risk-free rate equals 3.79% for the period 19950228 – 20050305, it equals 4.08% for the period 19900131 – 20050305; it equals 3.708% for the period 19920901 – 20050305. *Total Payoff* is the value at the end of the period of one dollar invested in the index at the beginning of the period (assuming dividend reinvestment).

	Average Return	Standard Deviation	Sharpe Ratio	Total Payoff
Dow Jones High Yield 10 (MUT) 19900131 - 20050831	10.47%	15.71%	0.41	4.23
Dow Jones Industrial (DJX) 19900131 – 20050831	12.02%	14.63%	0.54	5.51
S&P 100 (OEX) 19900131 - 20050831	10.53%	15.03%	0.43	4.33
S&P 500 (SPX) 19900131 - 20050831	11.13%	14.42%	0.49	4.83
Russell Midcap Growth (RDG) 19950228 - 20050831	12.50%	24.00%	0.36	2.75
Russell Midcap Value (RMV) 19950228 - 20050831	15.35%	14.32%	0.81	4.51
S&P Barra Growth (SGX) 19900131 - 20050831	10.39%	15.97%	0.40	4.15
S&P Barra Value (SVX) 19900131 – 20050831	8.33%	14.61%	0.29	3.10
S&P Barra Growth (SGX) 19950228 - 20050831	11.59%	16.91%	0.46	2.92
S&P Barra Value (SVX) 19950228 - 20050831	9.62%	15.75%	0.37	2.41
Russell 1000 Growth (RLG) 19920930 - 20050831	8.89%	17.77%	0.29	2.57
Russell 1000 Value (RLV) 19920930 - 20050831	10.77%	13.29%	0.53	3.60
Russell 2000 Growth (RUO) 19950228 - 20050831	16.32%	26.56%	0.47	3.84
Russell 2000 Value (RUJ) 19950228 – 20050831	17.23%	15.69%	0.86	5.37
Russell 3000 Growth (RAG) 19950228 – 20050831	9.68%	19.50%	0.30	2.27
Russell 3000 Value (RAV) 19950228 - 20050831	13.88%	14.77%	0.68	3.84

Table III
Difference in Risk Aversion for Five Growth-Value Index Pairs

We use prices of options on five pairs of growth and value indices to estimate risk aversion across wealth, daily. The five index pairs are: Russell Midcap Growth (RDG) and Value (RMV) for December 2003—December 2004; The Standard & Poor's Barra Growth (SGX) and Value (SVX) indices for January 1996—December 1998; Russell 1000 Growth (RLG) and Value (RLV) indices for November 2003—December 2004; Russell 2000 Growth (RUO) and Value (RUJ) for December 2003—July 2005; Russell 3000 Growth (RAG) and Value (RAV) for December 2003—July 2005. A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from index options. On each date we obtain risk aversion estimates for wealth levels ranging from 0.960 to 1.000 with step size of 0.001 (we use different wealth intervals for different index pairs depending on option data availability, but the step size is the same throughout). Using the Satterthwaite difference in means test, which accounts for unequal variances, and the Brown-Mood non-parametric difference in medians test, we test if the mean and median risk aversions of the two representative agents are equal. We perform the test for each wealth level.

Wealth	Growth	Value	Satterthwaite Mean Test		Brown-Mood Median Test		Largest RA
	Mean	Mean	t-value	p-value	Z-value	p-value	
Panel A: Russell Midcap Growth (RDG) and Value (RMV) Indices							
0.960	-10.09	9.58	-22.51	<.0001	12.14	<.0001	Value
0.965	-10.98	11.15	-25.72	<.0001	11.13	<.0001	Value
0.970	-11.84	9.48	-39.85	<.0001	10.10	<.0001	Value
0.975	-12.59	6.95	-49.55	<.0001	8.55	<.0001	Value
0.980	-12.97	4.31	-24.47	<.0001	7.29	<.0001	Value
0.985	-13.23	1.67	-13.72	<.0001	5.92	<.0001	Value
0.990	-13.4	-1.42	-8.63	<.0001	5.38	<.0001	Value
0.995	-12.48	-0.22	-7.76	<.0001	3.07	0.001	Value
1.000	-11.47	-6.06	-1.38	0.399	1.42	0.078	Value
Panel B: S&P Barra Growth (SGX) and Value (SVX) Indices							
0.980	6.23	-2.34	13.01	<.0001	7.87	<.0001	Growth
0.985	3.03	7.36	-7.13	<.0001	3.03	<.0001	Value
0.990	1.05	13.77	-22.22	<.0001	14.57	<.0001	Value
0.995	1.60	16.78	-26.89	<.0001	17.17	<.0001	Value
1.000	2.46	19.82	-31.69	<.0001	17.63	<.0001	Value
1.005	2.52	19.92	-30.84	<.0001	15.91	<.0001	Value
1.010	1.05	16.78	-27.62	<.0001	17.28	<.0001	Value
1.015	-1.58	8.67	-17.76	<.0001	12.24	<.0001	Value
1.020	-2.95	2.27	-8.37	<.0001	6.87	<.0001	Value

Table III—*Continued*

Wealth	Growth Mean	Value Mean	Satterthwaite Mean Test t-value	Satterthwaite Mean Test p-value	Brown-Mood Median Test Z-value	Brown-Mood Median Test p-value	Largest RA
Panel C: Russell 1000 Growth (RLG) and Value (RLV) Indices							
0.970	-14.48	3.48	-30.99	<.0001	-19.40	<.0001	Value
0.975	-16.75	3.32	-37.69	<.0001	-21.18	<.0001	Value
0.980	-18.86	1.79	-35.44	<.0001	-21.12	<.0001	Value
0.985	-20.49	-1.35	-31.36	<.0001	-21.14	<.0001	Value
0.990	-21.70	-5.38	-27.74	<.0001	-21.49	<.0001	Value
0.995	-20.77	-8.78	-25.33	<.0001	20.63	<.0001	Value
1.000	-18.03	-10.62	-17.31	<.0001	15.29	<.0001	Value
1.005	-13.82	-12.13	-4.72	<.0001	2.90	0.0018	Value
1.010	-8.852	-12.62	10.98	<.0001	-5.11	<.0001	Growth
Panel D: Russell 2000 Growth (RUO) and Value (RUJ) Indices							
0.980	-9.52	5.48	-19.17	<.0001	10.71	<.0001	Value
0.985	-9.14	2.79	-18.42	<.0001	10.94	<.0001	Value
0.990	-8.27	0.80	-18.71	<.0001	10.78	<.0001	Value
0.995	-7.15	1.50	-23.02	<.0001	12.20	<.0001	Value
1.000	-6.06	3.01	-21.81	<.0001	12.49	<.0001	Value
1.005	-4.82	4.58	-27.21	<.0001	12.37	<.0001	Value
1.010	-3.78	5.05	-29.08	<.0001	11.68	<.0001	Value
1.015	-2.81	6.01	-26.88	<.0001	10.21	<.0001	Value
1.020	-0.76	5.24	-19.34	<.0001	9.11	<.0001	Value
Panel E: Russell 3000 Growth (RAG) and Value (RAV) Indices							
0.980	-14.56	2.72	-24.75	<.0001	15.10	<.0001	Value
0.985	-14.95	5.02	-25.39	<.0001	14.69	<.0001	Value
0.990	-15.67	4.09	-25.73	<.0001	13.33	<.0001	Value
0.995	-15.39	0.64	-29.76	<.0001	13.12	<.0001	Value
1.000	-14.15	-2.55	-20.08	<.0001	12.24	<.0001	Value
1.005	-12.25	-3.62	-16.2	<.0001	10.62	<.0001	Value
1.010	-10.02	-2.93	-15.97	<.0001	9.83	<.0001	Value
1.015	-6.40	-1.87	-7.51	<.0001	5.17	<.0001	Value
1.020	-2.60	1.46	-3.65	0.0004	1.83	<.0001	Value

Table IV
Time Series Evidence: Autocorrelations in Estimated Risk Preference Parameters

The table reports autocorrelations in risk aversion coefficients estimated for investors in the S&P Barra Growth (SGX) and Value (SVX) Indices. For each index, Arrow-Pratt measure of risk aversion is estimated using options on the index and index returns. The procedure produces monthly risk aversion estimates. Subscript *G* denotes growth index and subscript *V* denotes value index. *p*-values are shown below correlation estimates. Panel A: autocorrelation in risk aversion. Panel B: Autocorrelation in market-adjusted risk aversion, computed as the difference in value or growth index risk aversion (at $w = 0.98$) and risk aversion for S&P 500 Index,

$$X_{G/V,t} = A_{G/V,t} - A_{S\&P500,t}.$$

Two adjustments are reported: using S&P 500 risk aversion estimates for wealth $w = 0.98$ and for $w = 1.00$. Panel C: risk aversion for S&P 100 Index is used for market adjustment.

Panel A: Autocorrelations in Risk Aversion

k =	$corr(A_{G,t}, A_{G,t-k})$	$corr(A_{V,t}, A_{V,t-k})$
1	0.82	0.82
	(0.000)	(0.000)
2	0.69	0.71
	(0.000)	(0.000)
3	0.63	0.63
	(0.000)	(0.000)
4	0.61	0.63
	(0.001)	(0.000)
5	0.49	0.69
	(0.009)	(0.000)
6	0.29	0.61
	(0.151)	(0.001)
7	0.16	0.54
	(0.443)	(0.006)
8	0.02	0.34
	(0.922)	(0.118)
9	-0.19	0.21
	(0.392)	(0.339)
10	-0.46	0.17
	(0.030)	(0.461)
11	-0.64	0.07
	(0.002)	(0.783)
12	-0.69	-0.02
	(0.001)	(0.933)

Table IV—*Continued*

Panel B: Autocorrelations in Risk Aversion Adjusted with the Market								
	$corr(X_{G,t}, X_{G,t-k})$ S&P 500 (*w*)		$corr(X_{V,t}, X_{V,t-k})$ S&P 500 (*w*)		$corr(X_{G,t}, X_{G,t-k})$ S&P 100 (*w*)		$corr(X_{V,t}, X_{V,t-k})$ S&P 100 (*w*)	
	w = 0.98	*w* = 1.00	*w* = 0.98	*w* = 1.00	*w* = 0.98	*w* = 1.00	*w* = 0.98	*w* = 1.00
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
k = 1	0.45	0.58	0.88	0.75	0.30	0.24	0.81	0.85
	(0.012)	(0.001)	(0.000)	(0.000)	(0.102)	(0.187)	(0.000)	(0.000)
k = 2	-0.05	0.42	0.85	0.60	0.02	-0.02	0.76	0.77
	(0.796)	(0.020)	(0.000)	(0.001)	(0.905)	(0.931)	(0.000)	(0.000)
k = 3	-0.10	0.48	0.81	0.60	0.15	0.05	0.71	0.70
	(0.620)	(0.008)	(0.000)	(0.001)	(0.436)	(0.804)	(0.000)	(0.000)
k = 4	0.20	0.31	0.74	0.62	0.20	0.17	0.68	0.70
	(0.306)	(0.104)	(0.000)	(0.001)	(0.300)	(0.398)	(0.000)	(0.000)
k = 5	0.37	0.14	0.74	0.66	0.14	0.07	0.60	0.68
	(0.059)	(0.494)	(0.000)	(0.000)	(0.486)	(0.730)	(0.001)	(0.000)
k = 6	0.24	0.03	0.63	0.71	0.19	-0.22	0.53	0.70
	(0.243)	(0.890)	(0.001)	(0.000)	(0.344)	(0.274)	(0.007)	(0.000)
k = 7	-0.18	-0.09	0.55	0.60	-0.15	-0.38	0.41	0.61
	(0.402)	(0.684)	(0.005)	(0.002)	(0.472)	(0.062)	(0.045)	(0.001)
k = 8	-0.08	-0.17	0.42	0.47	-0.38	-0.13	0.23	0.49
	(0.721)	(0.430)	(0.044)	(0.022)	(0.067)	(0.542)	(0.287)	(0.019)
k = 9	-0.10	-0.38	0.33	0.46	-0.19	0.05	0.20	0.36
	(0.655)	(0.073)	(0.131)	(0.033)	(0.377)	(0.816)	(0.372)	(0.097)
k = 10	-0.27	-0.54	0.32	0.38	0.25	0.00	0.20	0.33
	(0.218)	(0.01)	(0.164)	(0.091)	(0.272)	(0.999)	(0.385)	(0.147)
k = 11	-0.37	-0.60	0.28	0.30	0.03	-0.28	0.05	0.36
	(0.098)	(0.004)	(0.229)	(0.195)	(0.888)	(0.223)	(0.847)	(0.118)
k = 12	-0.39	-0.52	0.19	0.30	-0.051	0.04	-0.09	0.34
	(0.091)	(0.018)	(0.449)	(0.217)	(0.832)	(0.864)	(0.707)	(0.154)

Table V
Changes in Risk Preferences of Growth and Value Investors

The table reports regression results for the changes in risk aversion of growth (SGX) and value (SVX) investors. Growth index is S&P Barra Growth Index and the value index is S&P Barra Value Index. The dependent variable is the change in risk aversion (for a given wealth level) $\Delta RA_{G,t} = RA_{G,t} - RA_{G,t-1}$. Explanatory variables: $RET_{G,t-1}$ is the lag of the return on the growth index (SGX); $RET_{V,t-1}$ is the lag of the return on the value index (SVX); $RA_{G,t-1}$ and $RA_{V,t-1}$ are the lags of the risk aversion level; *t*-statistics are reported below coefficient estimates.

Panel A

	$\Delta RA_{G,t} = RA_{G,t} - RA_{G,t-1}$			
Intercept	0.331	1.346	0.574	1.687
	0.34	1.19	0.60	1.51
$RET_{G,t-1}$	-99.57**	-92.11**	-106.55**	-94.74**
	-2.34	-2.21	-2.57	-2.34
$RET_{V,t-1}$	136.31***	127.25**	146.42***	133.04***
	2.67	2.55	2.95	2.75
$RA_{G,t-1}$		-0.162		-0.175 *
		-1.65		-1.75
$\Delta RA_{G,t-1}$			-0.202	-0.103
			-1.18	-0.59
$AdjR^2$	14.5%	19.5%	17.9%	23.9%
D.W.	2.12	1.98	2.05	2.07
N Obs.	31	31	30	30

Panel B

	$\Delta RA_{V,t} = RA_{V,t} - RA_{V,t-1}$			
Intercept	-0.858	-0.833	-0.961	-0.944
	-0.58	-0.57	-0.63	-0.62
$RET_{G,t-1}$	117.60*	98.98	104.83	93.79
	1.85	1.52	1.58	1.38
$RET_{V,t-1}$	-140.26*	-121.93	-130.52	-119.01
	-1.81	-1.55	-1.63	-1.46
$RA_{V,t-1}$		-0.134		-0.117
		-1.18		-0.94
$\Delta RA_{V,t-1}$			-0.166	-0.096
			-0.84	-0.45
$AdjR^2$	5.2%	6.5%	3.9%	3.4%
D.W.	2.27	2.11	2.01	1.99
N Obs.	30	30	29	29

Table VI
Return Variances and Changes in Risk Preferences of Growth and Value Investors

The table reports regression results for the changes in risk aversion of growth (SGX) and value (SVX) investors. Growth index is S&P Barra Growth Index and the value index is S&P Barra Value Index. The dependent variable is the change in risk aversion (for a given wealth level) $\Delta RA_{G/V,t} = RA_{G/V,t} - RA_{G/V,t-1}$. Panel A reports results for growth index and Panel B for the value index. Explanatory variables: $RET_{G,t-1}$ is the lag of the return on the growth index (SGX); $RET_{V,t-1}$ is the lag of the return on the value index (SVX); $RA_{G,t-1}$ and $RA_{V,t-1}$ are the lags of the risk aversion level; $IVC_{G/V,t-1}$ is implied volatility for call options on the growth (*G*) or value (*V*) index; $S_{G/V,t}$ is annualized standard deviation of daily returns on the corresponding index for month *t*. *t*-statistics are reported below coefficient estimates.

				Panel A: Growth				
Intercept	3.762	4.627	-0.772	3.143	7.084	5.695*	3.478	4.297
	0.80	1.45	-0.14	0.89	1.53	1.88	0.59	1.18
$RET_{G,t-1}$	-90.3**	-91.4**	-96.9**	-90.1**	-89.9**	-98.6**	-91.78**	-94.99**
	-2.02	-2.16	-2.20	-2.13	-2.13	-2.46	-2.17	-2.33
$RET_{V,t-1}$	126.4**	113.5**	132.1**	118.6**	129.0**	121.1**	130.15**	123.50**
	2.37	2.15	2.53	2.23	2.58	2.43	2.60	2.45
$IVC_{G,t-1}$	-15.71		10.66		-29.57		-9.06	
	-0.74		0.39		-1.44		-0.31	
$S_{G,t-1}$		-25.87		-12.35		-30.74*		-18.53
		-1.42		-0.54		-1.77		-0.75
$RA_{G,t-1}$			-0.195	-0.121			-0.143	-0.100
			-1.49	-0.97			-0.99	-0.71
$\Delta RA_{G,t-1}$					-0.225	-0.246	-0.128	-0.172
					-1.33	-1.47	-0.66	-0.87
$AdjR^2$	13.2%	17.5%	16.9%	17.3%	21.2%	24.1%	21.1%	22.6%
D.W.	2.14	2.16	1.95	2.02	2.12	2.13	2.08	2.08
N Obs.	31	31	31	31	30	30	30	30

Table VI – *Continued*

Panel B: Value								
Intercept	1.161	9.69**	12.61*	12.40***	0.989	10.24**	12.800	12.33***
	0.22	2.25	1.78	2.98	0.17	2.34	1.57	2.88
$RET_{G,t-1}$	120.4	132.6**	86.81	104.2*	107.0	116.0**	86.70	98.24*
	1.85*	2.28	1.40	1.89	1.57	1.95	1.33	1.71
$RET_{V,t-1}$	-142.71*	-197.2***	-107.9	-179.9***	-132.3	-186.7**	-107.7	-176.4**
	-1.81	-2.67	-1.44	-2.61	-1.62	-2.50	-1.37	-2.48
$IVC_{V,t-1}$	-10.08		-66.93*		-9.64		-67.8*	
	-0.39		-1.94		-0.35		-1.71	
$S_{V,t-1}$		-74.38**		-93.2***		-78.9***		-93.4***
		-2.58		-3.33		-2.70		-3.25
$RA_{V,t-1}$			-0.355**	-0.232**			-0.357*	-0.210*
			-2.26	-2.31			-1.93	-1.92
$\Delta RA_{V,t-1}$					-0.173	-0.231	-0.001	-0.116
					-0.86	-1.29	-0.01	-0.65
$AdjR^2$	2.1%	21.5%	15.5%	32.7%	0.4%	23.2%	10.6%	30.9%
D.W.	2.29	2.23	2.10	2.09	2.01	1.85	2.09	1.92
N Obs.	30	30	30	30	29	29	29	29

Table VII
Autocorrelations in Mutual Fund Flows

The table reports autocorrelations in fund flows to growth and value mutual funds. The aggregate monthly data is from TrimTabs for the period 02-1999 through 11-1006. The aggregate data covers flows to mutual funds in growth and value Morningstar categories. Panel A reports autocorrelations in aggregate flow data for the whole period and for two sub-periods. Panel B reports results for Kemper large capitalization growth and value funds, using fund-level data. Panel B reports autocorrelations in flows to three Oppenheimer mutual funds, using fund-level data for two growth funds and one value fund. Subscript *G* denotes growth and subscript *V* denotes value. *p*-values are shown below correlation estimates.

Panel A: Autocorrelations in Aggregate Flows to Growth and Value Mutual Funds

	Full Sample: 021999–112006 $corr(F_{G/V,t}, F_{G/V,t-k})$		Sub-sample: 021999—122002 $corr(F_{G/V,t}, F_{G/V,t-k})$		Sub-sample: 012003—112006 $corr(F_{G/V,t}, F_{G/V,t-k})$	
k=	Growth	Value	Growth	Value	Growth	Value
1	0.54	0.67	0.55	0.60	0.51	0.64
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2	0.36	0.55	0.33	0.44	0.43	0.58
	(0.001)	(0.000)	(0.029)	(0.002)	(0.003)	(0.000)
3	0.27	0.54	0.19	0.45	0.42	0.50
	(0.009)	(0.000)	(0.222)	(0.002)	(0.005)	(0.001)
4	0.12	0.48	-0.01	0.37	0.32	0.49
	(0.263)	(0.000)	(0.973)	(0.016)	(0.039)	(0.001)
5	0.10	0.53	0.03	0.49	0.20	0.34
	(0.340)	(0.000)	(0.844)	(0.001)	(0.197)	(0.026)
6	0.06	0.47	-0.10	0.44	0.22	0.30
	(0.569)	(0.000)	(0.549)	(0.004)	(0.175)	(0.059)
7	-0.001	0.42	-0.17	0.39	0.07	0.22
	(0.996)	(0.000)	(0.287)	(0.014)	(0.656)	(0.167)
8	-0.06	0.37	-0.17	0.31	0.04	0.22
	(0.573)	(0.001)	(0.297)	(0.06)	(0.800)	(0.184)
9	-0.13	0.38	-0.11	0.51	-0.07	0.11
	(0.245)	(0.000)	(0.499)	(0.001)	(0.658)	(0.510)
10	-0.02	0.45	0.008	0.65	0.12	0.14
	(0.853)	(0.000)	(0.965)	(0.000)	(0.462)	(0.393)
11	-0.17	0.33	-0.146	0.44	-0.02	0.10
	(0.114)	(0.002)	(0.396)	(0.007)	(0.886)	(0.571)
12	-0.17	0.27	-0.17	0.32	0.06	0.26
	(0.127)	(0.013)	(0.326)	(0.059)	(0.722)	(0.137)
13	-0.24	0.21	-0.27	0.23	0.01	0.08
	(0.029)	(0.057)	(0.121)	(0.181)	(0.971)	(0.635)
14	-0.34	0.19	-0.45	0.23	-0.03	0.09
	(0.002)	(0.091)	(0.009)	(0.203)	(0.879)	(0.604)
15	-0.33	0.17	-0.41	0.28	0.01	0.01
	(0.003)	(0.133)	(0.018)	(0.127)	(0.977)	(0.977)
16	-0.25	0.22	-0.36	0.34	0.05	0.16
	(0.030)	(0.054)	(0.048)	(0.064)	(0.805)	(0.378)
17	-0.29	0.13	-0.45	0.10	-0.05	0.07
	(0.009)	(0.272)	(0.012)	(0.593)	(0.780)	(0.703)
18	-0.25	0.05	-0.26	0.09	-0.06	-0.08
	(0.029)	(0.670)	(0.167)	(0.657)	(0.767)	(0.664)

Table VII – *Continued*

The panels report autocorrelations in flows in growth and value mutual funds. Panel B: Growth funds are Kemper large capitalization growth funds (3, 112, 12, 203, 303, 503). Value funds are Kemper large capitalization value funds (86, 286, 386, 586). For growth and value funds we compute the net value traded (net cash flow) over the month starting January 1995 and ending December 1999. Panel C: Growth 1 is Oppenheimer Enterprise (a large capitalization growth fund); Growth 2 is Oppenheimer Growth fund (A & B share classes); Value fund is Oppenheimer Quest Value fund (share classes A and B); net flows are computed over the period February 1998 through February 2001. Subscript *G* denotes growth and subscript *V* denotes value. *p*-values are shown below correlation estimates.

	Panel B: Kemper Funds		Panel C: Oppenheimer Funds		
	Growth	Value	Growth 1	Growth 2	Value
k =	$corr(F_{G,t}, F_{G,t-k})$	$corr(F_{V,t}, F_{V,t-k})$	$corr(F_{G,t}, F_{G,t-k})$	$corr(F_{G,t}, F_{G,t-k})$	$corr(F_{V,t}, F_{V,t-k})$
1	0.27	0.72	0.51	0.42	0.82
	(0.038)	(0.000)	(0.002)	(0.012)	(0.000)
2	0.44	0.61	0.54	0.56	0.76
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
3	0.41	0.46	0.33	0.37	0.68
	(0.002)	(0.001)	(0.064)	(0.034)	(0.000)
4	0.15	0.37	0.09	0.49	0.63
	(0.259)	(0.009)	(0.607)	(0.005)	(0.000)
5	0.34	0.43	0.06	0.34	0.53
	(0.011)	(0.003)	(0.763)	(0.060)	(0.002)
6	0.24	0.27	-0.07	0.34	0.51
	(0.075)	(0.074)	(0.711)	(0.067)	(0.004)
7	0.22	0.06	-0.07	0.25	0.39
	(0.107)	(0.713)	(0.721)	(0.196)	(0.037)
8	-0.05	0.23	-0.12	0.24	0.33
	(0.704)	(0.127)	(0.556)	(0.218)	(0.082)
9	-0.01	0.36	-0.05	0.39	0.21
	(0.925)	(0.017)	(0.786)	(0.044)	(0.299)
10	-0.21	0.31	-0.21	0.01	0.12
	(0.149)	(0.048)	(0.303)	(0.953)	(0.558)
11	-0.03	0.16	-0.32	0.04	0.08
	(0.819)	(0.330)	(0.125)	(0.862)	(0.702)
12	-0.25	0.04	-0.39	-0.15	0.20
	(0.092)	(0.809)	(0.059)	(0.490)	(0.346)
13	-0.31	0.09	-0.68	-0.18	0.16
	(0.036)	(0.586)	(0.000)	(0.412)	(0.472)
14	-0.46	0.10	-0.72	-0.24	0.15
	(0.001)	(0.550)	(0.000)	(0.280)	(0.503)
15	-0.28	0.14	-0.64	-0.02	-0.10
	(0.070)	(0.412)	(0.002)	(0.933)	(0.663)
16	-0.32	0.25	-0.50	0.02	-0.27
	(0.034)	(0.147)	(0.025)	(0.945)	(0.249)
17	-0.33	0.18	-0.24	0.15	-0.31
	(0.032)	(0.295)	(0.323)	(0.545)	(0.190)
18	-0.13	0.20	-0.08	-0.06	-0.32
	(0.411)	(0.260)	(0.750)	(0.799)	(0.190)

Table VIII
Mutual Fund Flows to Growth and Value Funds

The table reports regression results for fund flows to growth and value mutual funds. Fund flow data is from TrimTabs for the period from February 1999 through November 2006. Panel A reports results for flows to growth mutual funds. Panel B reports results for flows to value funds. Panel C reports the results of regressions of the switching factor, PC_S, on returns and risks. Lagged values are included to control for serial correlation, $XFL_{G/V,t}$ is flow to the growth/value funds in month t. $RET_{G,t}$ is return on the growth funds computed for month t as the average of daily returns in the month; We use two measures of risk: S is the standard deviation of daily returns on the growth or value style in a given month; r^2 is the average of squared daily returns in a given month. *t*-statistics are reported below coefficient estimates.

Panel A: Flow to Growth Funds					
Intercept	144.8	499.2*	302.9**	250.7	187.6
	1.58	1.96	2.13	0.94	1.28
$XFL_{G,t-1}$	0.450***	0.614***	0.597***	0.487***	0.480***
	4.55	6.63	6.49	4.71	4.53
$RET_{G,t-1}$	65297**			56089*	61714*
	2.12			1.63	1.75
$RET_{G,t-2}$	61363**			67332**	61883*
	1.93			1.98	1.76
$RET_{V,t-1}$	-166036***			-167395***	-161529***
	-3.13			-2.98	-2.76
$RET_{V,t-2}$	7073			1867	13084
	0.13			0.03	0.24
$S_{G,t-1}$		-25381		-21327	
		-1.27		-1.05	
$S_{G,t-2}$		24354		37447*	
		1.21		1.87	
$S_{V,t-1}$		-38967*		-20866	
		-1.79		-0.96	
$S_{V,t-2}$		-5169		-16485	
		-0.24		-0.76	
$r^2_{G,t-1}$			-467859		-279059
			-1.05		-0.61
$r^2_{G,t-2}$			291053		563015
			0.66		1.27
$r^2_{V,t-1}$			-1448145**		-675308
			-2.04		-0.92
$r^2_{V,t-2}$			-184385		-475969
			-0.26		-0.66
$AdjR^2$	35.3%	30.9%	30.4%	36.0%	34.5%
D.W.	2.14	2.05	2.10	2.11	2.15
N.Obs.	90	90	90	90	90

Table VIII – *Continued*

			Panel B: Flow to Value Funds		
Intercept	224.3**	807.4***	528.5***	834.4***	536.1***
	1.98	2.98	3.27	2.53	2.74
$XFL_{G,t-1}$	0.709***	0.687***	0.669***	0.670***	0.674***
	8.39	8.51	8.52	6.53	6.83
$RET_{G,t-1}$	5146			-57200	-52271
	0.15			-1.59	-1.43
$RET_{G,t-2}$	22620			18059	9222
	0.69			0.55	0.27
$RET_{V,t-1}$	-9539			10884	27138
	-0.17			0.20	0.48
$RET_{V,t-2}$	82493			26665	46515
	1.53			0.51	0.88
$S_{G,t-1}$		-45635**		-56451***	
		-2.42		-2.67	
$S_{G,t-2}$		25687		30920	
		1.27		1.47	
$S_{V,t-1}$		-47771**		-46609**	
		-2.19		-2.07	
$S_{V,t-2}$		14668		20382	
		0.70		0.94	
$r^2_{G,t-1}$			-959779**		-1130066***
			-2.26		-2.40
$r^2_{G,t-2}$			390988		489668
			0.88		1.05
$r^2_{V,t-1}$			-1759785***		-1863858***
			-2.52		-2.54
$r^2_{V,t-2}$			380497		497910
			0.55		0.69
$AdjR^2$	46.9%	53.7%	52.4%	54.2%	52.8
D.W.	2.36	2.21	2.24	2.27	2.32
N.Obs.	90	90	90	90	90

Table VIII – *Continued*

Panel C: Switching Factor					
Intercept	-0.007	0.024	0.020	-0.193	-0.085
	-0.15	0.17	0.26	-1.22	-1.00
$PC_{S,t-1}$	0.778***	0.787***	0.797***	0.677***	0.699***
	12.70	10.82	11.25	8.36	8.73
$RET_{G,t-1}$	42.26***			66.25***	64.93***
	2.64			3.49	3.38
$RET_{G,t-2}$	9.51			23.23	20.52
	0.59			1.25	1.07
$RET_{V,t-1}$	-78.82***			-96.80***	-97.48***
	-3.02			-3.57	-3.50
$RET_{V,t-2}$	-0.26			7.51	7.91
	-0.01			0.28	0.29
$S_{G,t-1}$		1.22		12.36	
		0.11		1.07	
$S_{G,t-2}$		2.13		9.84	
		0.20		0.94	
$S_{V,t-1}$		0.84		7.67	
		0.07		0.69	
$S_{V,t-2}$		-9.89		-20.54*	
		-0.86		-1.84	
$r^2_{G,t-1}$			38.4		289.8
			0.16		1.12
$r^2_{G,t-2}$			-36.9		128.2
			-0.16		0.55
$r^2_{V,t-1}$			-29.0		377.5
			-0.08		1.03
$r^2_{V,t-2}$			-292.2		-554.0
			-0.79		-1.51
$AdjR^2$	67.4%	63.3%	63.3%	68.2%	67.7%
D.W.	2.30	2.09	2.11	2.29	2.29
N.Obs.	90	90	90	90	90

Table IX
Performance of Trading Strategies

The table reports results for several option trading strategies for each of the five growth and value index pairs: Russell Midcap Growth (RDG) and Value (RMV); The Standard & Poor's Barra Growth (SGX) and Value (SVX); Russell 1000 Growth (RLG) and Value (RLV); Russell 2000 Growth (RUO) and Value (RUJ); Russell 3000 Growth (RAG) and Value (RAV). PORTFOLIO column reports the results for an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV). Data range is November 2003 through December 2004 for the last four index pairs, and January 1996 through January 1999 for SGX/SVX. Strategy 1 involves selling two call options on the growth index with strikes nearest to the current index value, and investing the proceeds in two call options on the corresponding value index with strike prices nearest to the current index value. Strategy 2 involves selling a straddle on the growth index (a call and a put with the same strike) with the strike closest to the current index value and buying a straddle on the corresponding value index. All strategies require zero initial investment. *Value* is the ending dollar value of the strategy; *Average* is the average payoff on the strategy across all periods; *St. Dev.* is the standard deviation of payoffs across the period; *Min.* and *Max.* are the minimum and the maximum payoffs, respectively, across the periods. All numbers are in dollars.

	PORTFOLIO	SGX/SVX	RDG/RMV	RLG/RLV	RUO/RUJ	RAG/RAV
Strategy 1: Short Calls on Growth and Long Calls on Value						
Dollar Value	81.68	150.25	70.50	62.09	103.84	90.28
Average payoff	6.28	4.17	5.42	4.78	7.99	6.94
St. Dev. Payoff	10.06	15.12	12.18	11.23	12.67	11.6
t-Statistic	2.25	1.65	1.61	1.53	2.27	2.16
Min.	-14.60	-26.43	-24.97	-22.84	-20.60	-17.63
Max.	26.13	43.52	25.13	28.33	20.63	30.91
Strategy 2: Short a Straddle on Growth and Long a Straddle on Value						
Dollar Value	58.02	107.73	45.28	27.99	91.29	67.50
Average payoff	4.46	2.99	3.48	2.15	7.02	5.19
St. Dev. Payoff	5.07	10.27	5.9	6.46	6.52	6.07
t-Statistic	3.17	1.75	2.13	1.20	3.88	3.08
Min.	-2.97	-16.03	-5.64	-13.36	-4.12	-3.69
Max.	11.92	30.47	11.77	13.64	15.91	15.73

Table X
Performance of Trading Strategies with Transaction Costs

The table reports results for several option trading strategies for each of the five growth and value index pairs: Russell Midcap Growth (RDG) and Value (RMV); The Standard & Poor's Barra Growth (SGX) and Value (SVX); Russell 1000 Growth (RLG) and Value (RLV); Russell 2000 Growth (RUO) and Value (RUJ); Russell 3000 Growth (RAG) and Value (RAV). PORTFOLIO column reports the results for an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV). Data range is November 2003 through December 2004 for the last four index pairs, and January 1996 through January 1999 for SGX/SVX. Strategy 1 involves selling two call options on the growth index with strikes nearest to the current index value, and investing the proceeds in two call options on the corresponding value index with strike prices nearest to the current index value. Strategy 2 involves selling a straddle on the growth index (a call and a put with the same strike) with the strike closest to the current index value and buying a straddle on the corresponding value index. All strategies require zero initial investment. All buying is at ask prices and selling is at bid. *Value* is the ending dollar value of the strategy; *Average* is the average payoff on the strategy across all periods; *St. Dev.* is the standard deviation of payoffs across the period; *Min.* and *Max*. are the minimum and the maximum payoffs, respectively, across the periods. All numbers are in dollars.

	PORTFOLIO	SGX/SVX	RDG/RMV	RLG/RLV	RUO/RUJ	RAG/RAV
Strategy 1: Short Calls on Growth and Long Calls on Value						
Dollar Value	44.86	64.44	18.33	30.39	82.47	48.27
Average payoff	3.45	1.79	1.41	2.34	6.34	3.71
St. Dev. Payoff	10.13	13.74	12.54	10.24	12.84	11.67
t-Statistic	1.23	0.78	0.41	0.82	1.78	1.15
Min.	-19.64	-34.12	-31.11	-22.84	-22.19	-22.99
Max.	22.57	34.04	21.29	25.48	17.67	25.85
Strategy 2: Short a Straddle on Growth and Long a Straddle on Value						
Dollar Value	29.80	45.08	4.93	8.74	74.03	31.49
Average payoff	2.29	1.25	0.38	0.67	5.69	2.42
St. Dev. Payoff	5.12	9.87	5.82	6.10	6.67	5.82
t-Statistic	1.61	0.76	0.24	0.40	3.08	1.50
Min.	-5.44	-20.60	-11.77	-13.54	-4.35	-5.28
Max.	9.96	21.98	9.52	12.11	14.94	12.12

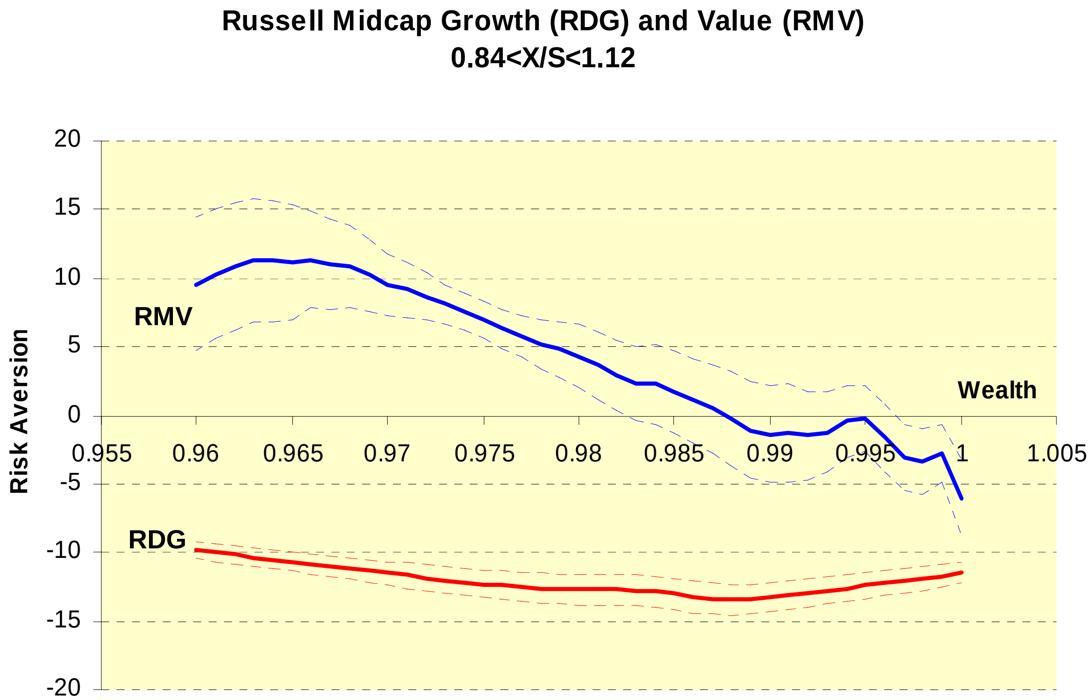

Figure 1. Risk aversion functions across wealth RDG and RMV indices
For the period from December 2003, through December 2004, we calculate the risk aversion function across wealth for two indices, Russell Midcap Growth (RDG) and Russell Midcap Value (RMV). A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from options on the indices. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

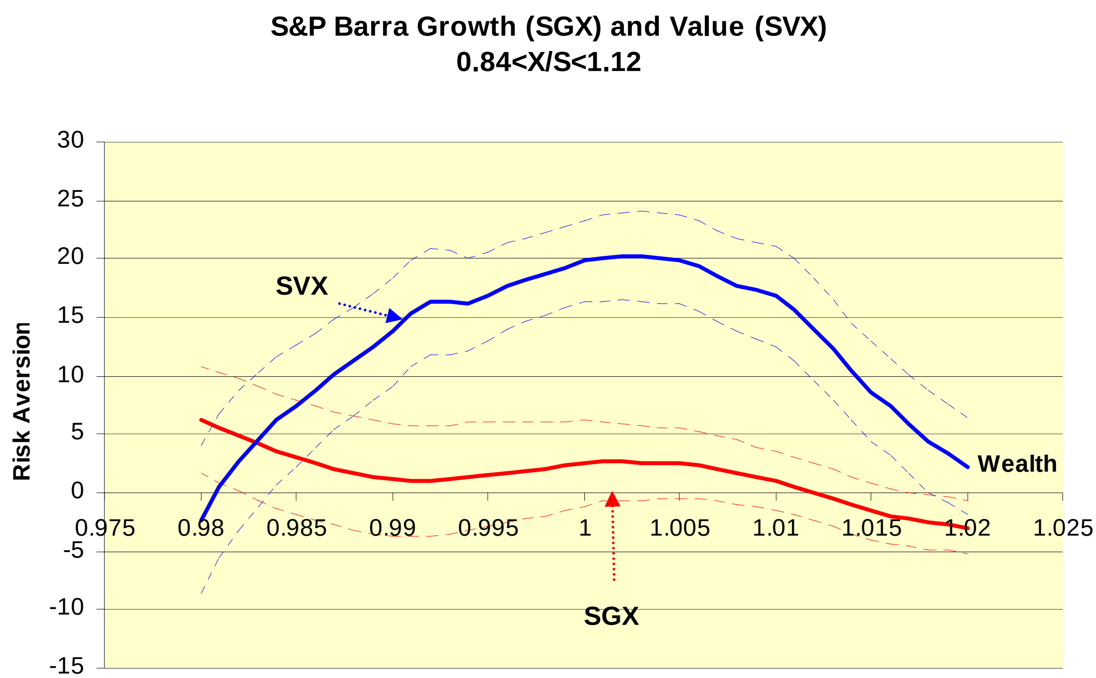

Figure 2. Risk aversion functions across wealth SGX and SVX indices

For the period from January 1996, through December 1998, we calculate the risk aversion function across wealth for two indices, The Standard & Poor's Barra Growth Index (SGX) and The Standard & Poor's Barra Value Index (SVX). A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from options on the indices. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

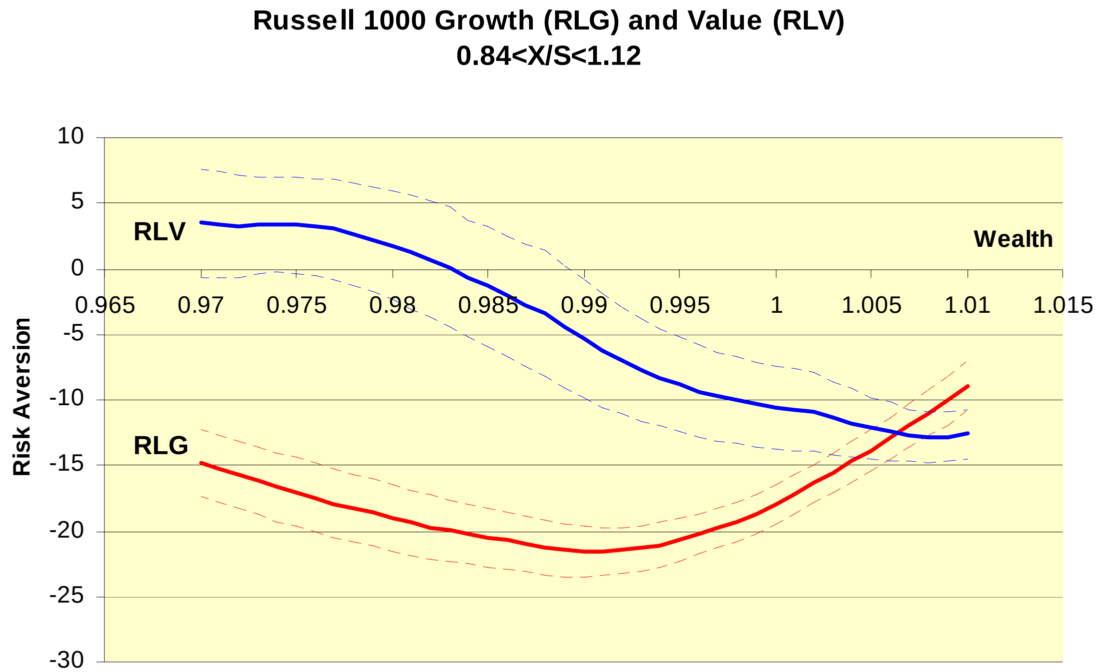

Figure 3. Risk aversion functions across wealth RLG and RLV indices
For the period from November 2003, through December 2004, we calculate the risk aversion function across wealth for two indices, Russell 1000 Growth Index (RLG) and Russell 1000 Value Index (RLV). A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from options on the indices. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

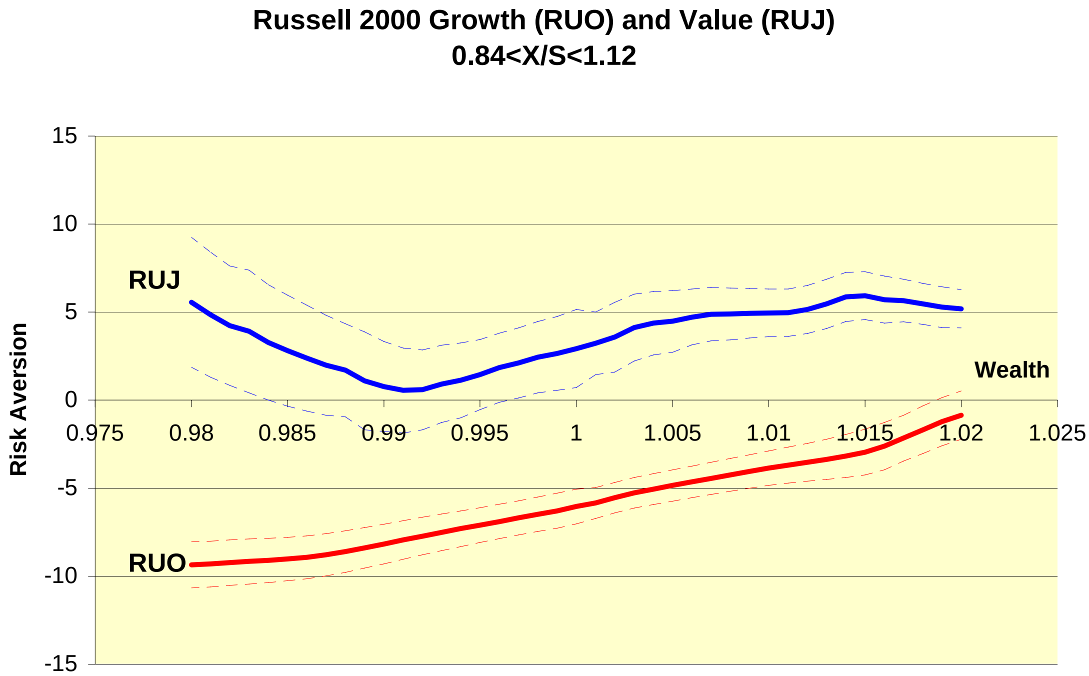

Figure 4. Risk aversion functions across wealth RUO and RUJ indices

For the period from December 2003, through July 2005, we calculate the risk aversion function across wealth for two indices, Russell 2000 Growth Index (RUO) and Russell 2000 Value Index (RUJ). A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from options on the indices. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

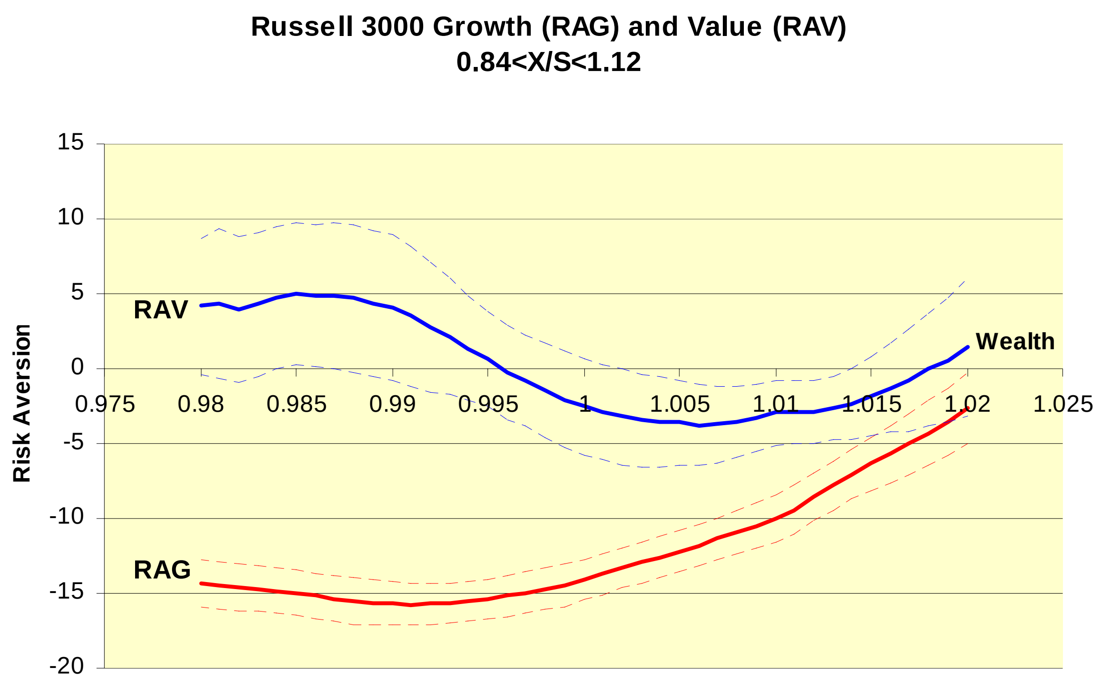

Figure 5. Risk aversion functions across wealth RAG and RAV indices

For the period from December 2003, through July 2005, we calculate the risk aversion function across wealth for two indices, Russell 3000 Growth Index (RAG) and Russell 3000 Value Index (RAV). A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from options on the indices. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

Figure 6A
Performance of Call Options Trading Strategies

The plots display total value and per period profit (loss) from option trading strategies on five growth and value index pairs. The strategy requires zero initial investment and involves selling two call options on the growth index and buying two call options on the value index. Trading is at the mid-point of the bid-ask spread. Portfolio strategy is an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV).

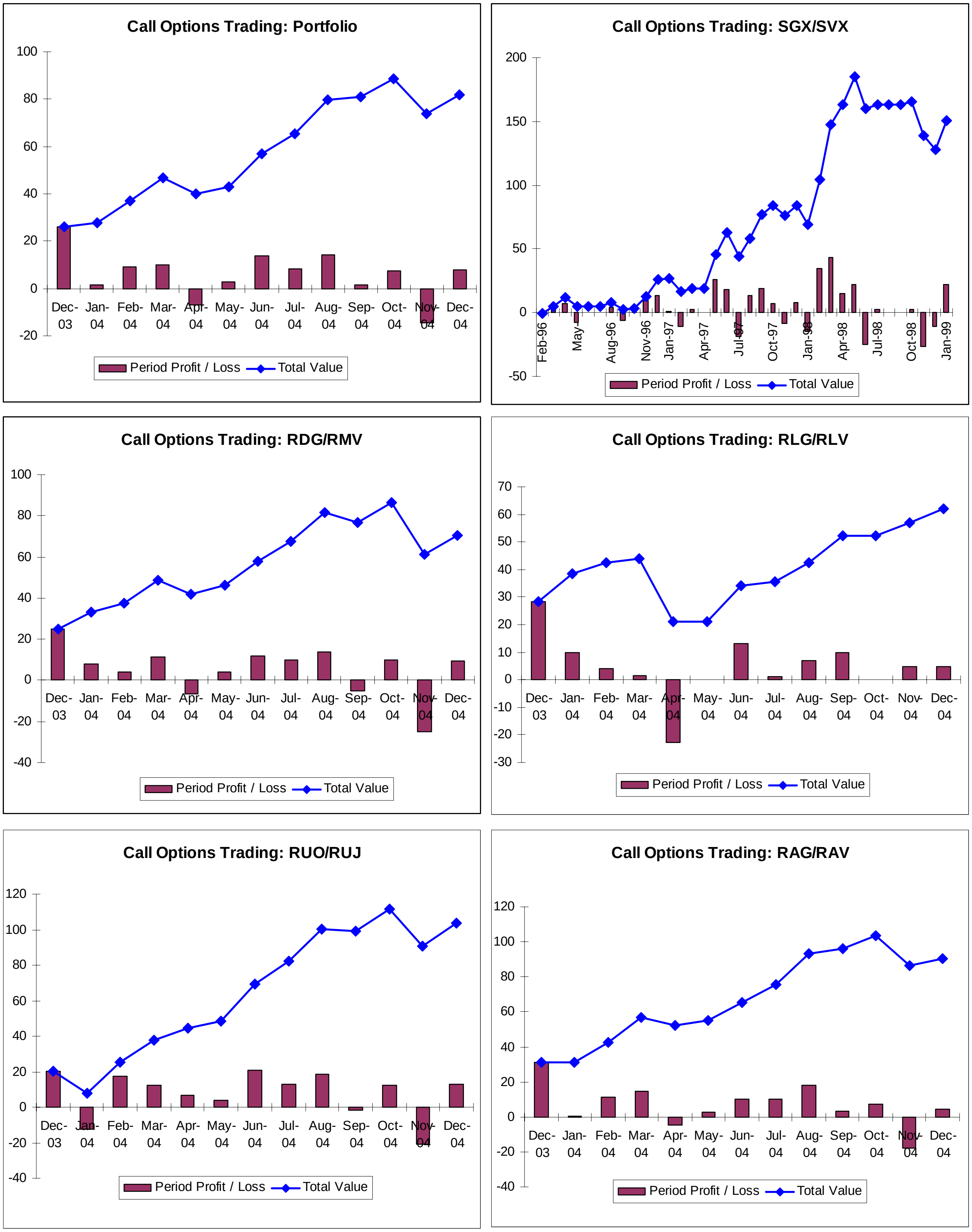

Figure 6B
Performance of Straddle Trading Strategies

The plots display total value and per period profit (loss) from option trading strategies on five growth and value index pairs. The strategy requires zero initial investment and involves selling a straddle on the growth index and buying a straddle on the value index. Trading is at the mid-point of the bid-ask spread. Portfolio strategy is an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV).

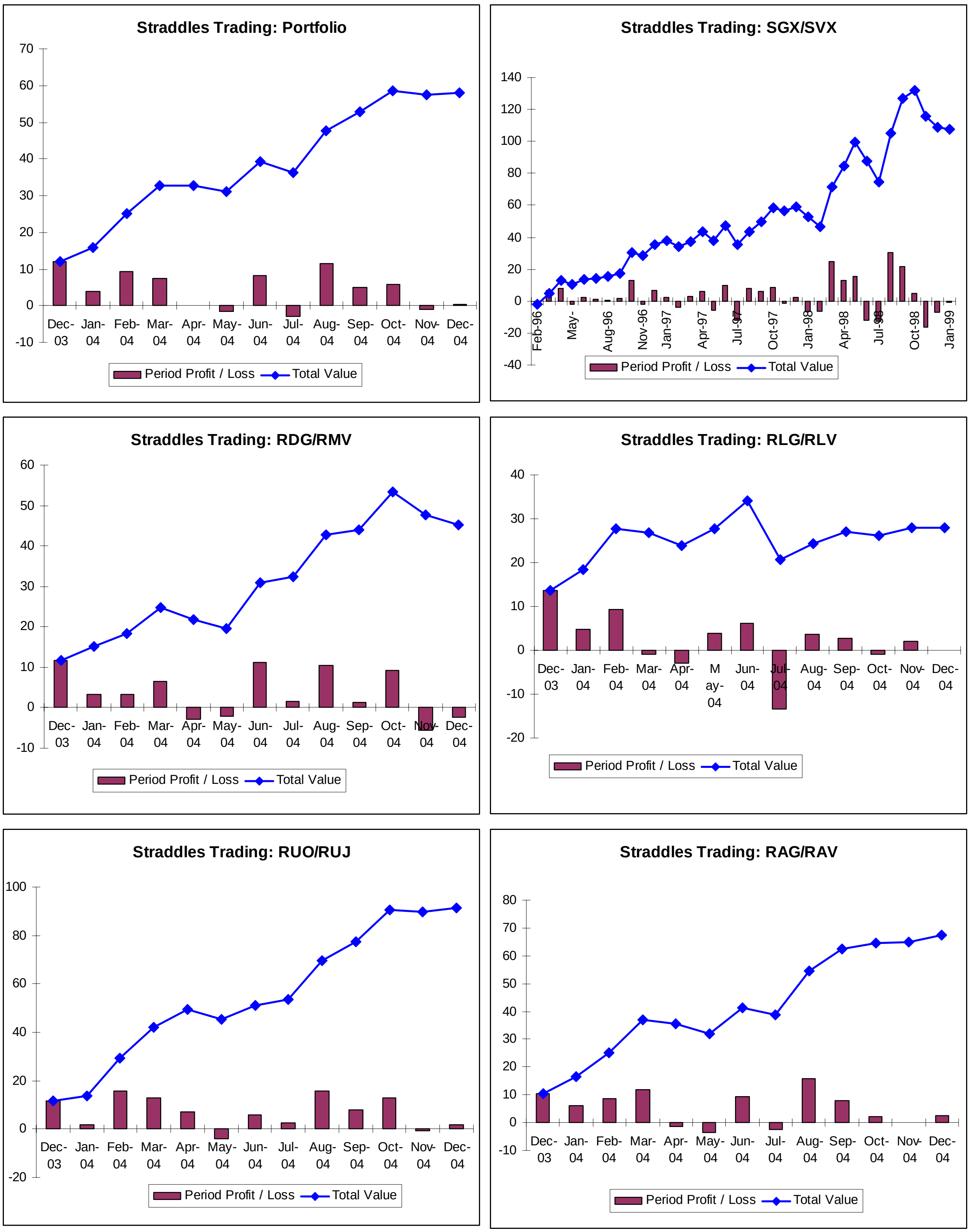

Figure 7A

Performance of Call Options Trading Strategies with Transaction Costs

The plots display total value and per period profit (loss) from option trading strategies on five growth and value index pairs. The strategy requires zero initial investment and involves selling two call options on the growth index and buying two call options on the value index. All buying is at ask prices and selling is at bid. Portfolio strategy is an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV).

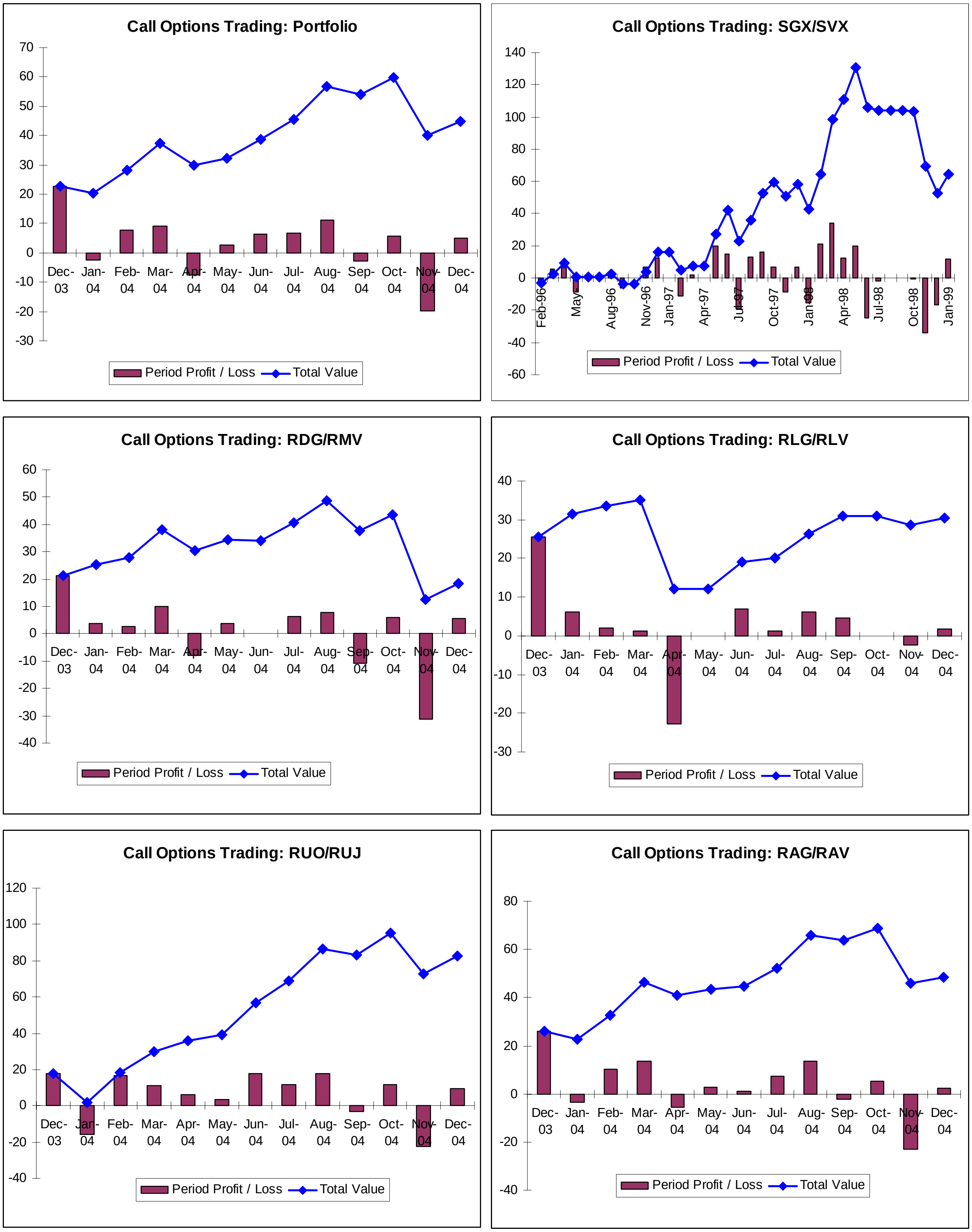

Figure 7B

Performance of Straddle Trading Strategies with Transaction Costs

The plots display total value and per period profit (loss) from option trading strategies on five growth and value index pairs. The strategy requires zero initial investment and involves selling a straddle on the growth index and buying a straddle on the value index. All buying is at ask prices and selling is at bid. Portfolio strategy is an equal-weighted portfolio of four pairs for which data is available for the same time period (RDG/RMV, RLG/RLV, RUO/RUJ, RAG/RAV).

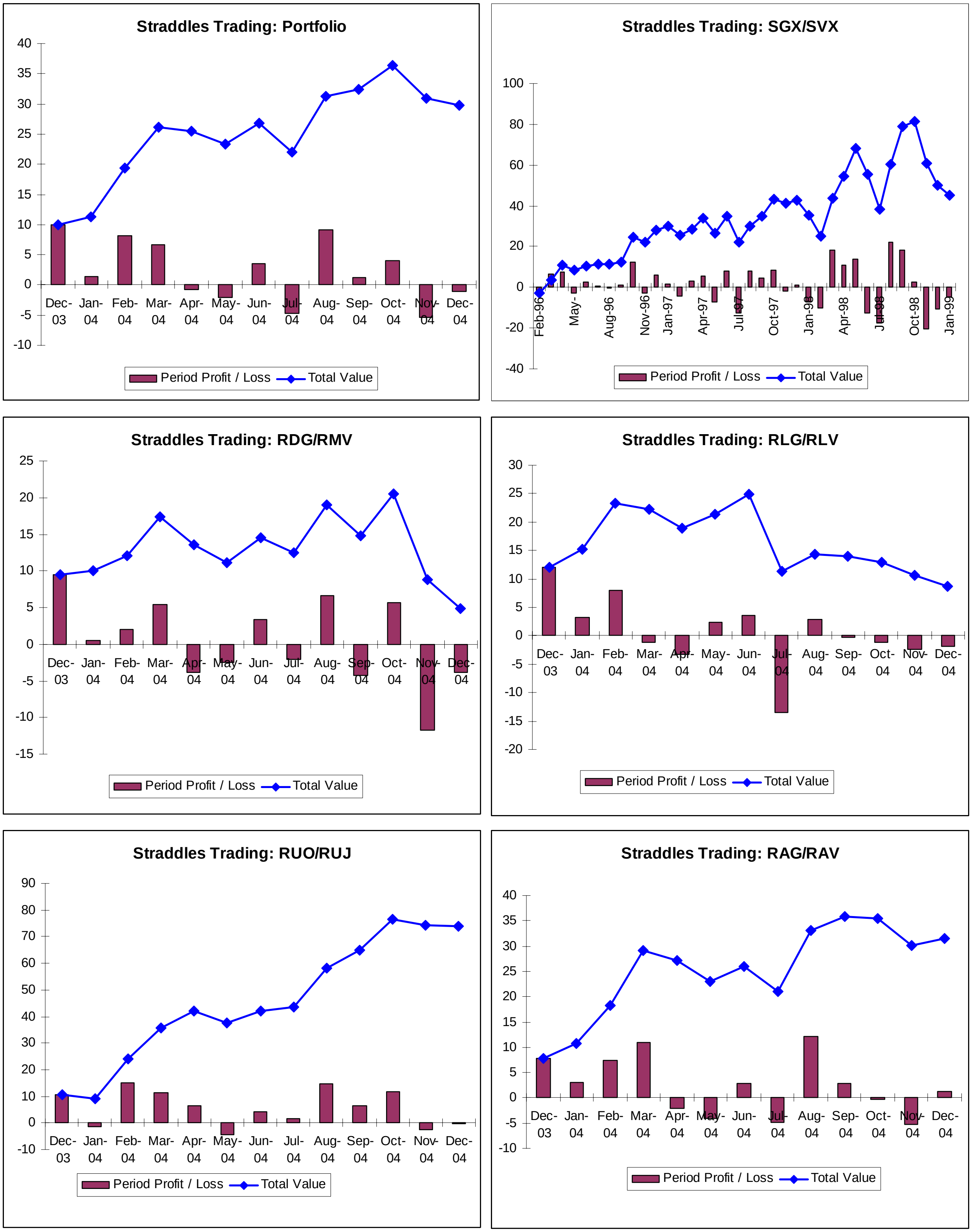

Figure B1
Risk Aversion for Five Growth-Value Index Pairs

We calculate risk aversion function across wealth for five pairs of indices: Russell Midcap Growth (RDG) and Value (RMV) for December 2003—December 2004; The Standard & Poor's Barra Growth (SGX) and Value (SVX) indices for January 1996—December 1998; Russell 1000 Growth (RLG) and Value (RLV) indices for November 2003—December 2004; Russell 2000 Growth (RUO) and Value (RUJ) for December 2003—July 2005; Russell 3000 Growth (RAG) and Value (RAV) for December 2003—July 2005. A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from index options. True distribution is estimated using returns that are lagged by 6 months relative to the date when risk aversion is estimated. For each wealth level, the mean risk aversion of daily estimates across the period is computed. In addition, the empirical standard deviation is computed. The graph displays the means and the standard deviation bound.

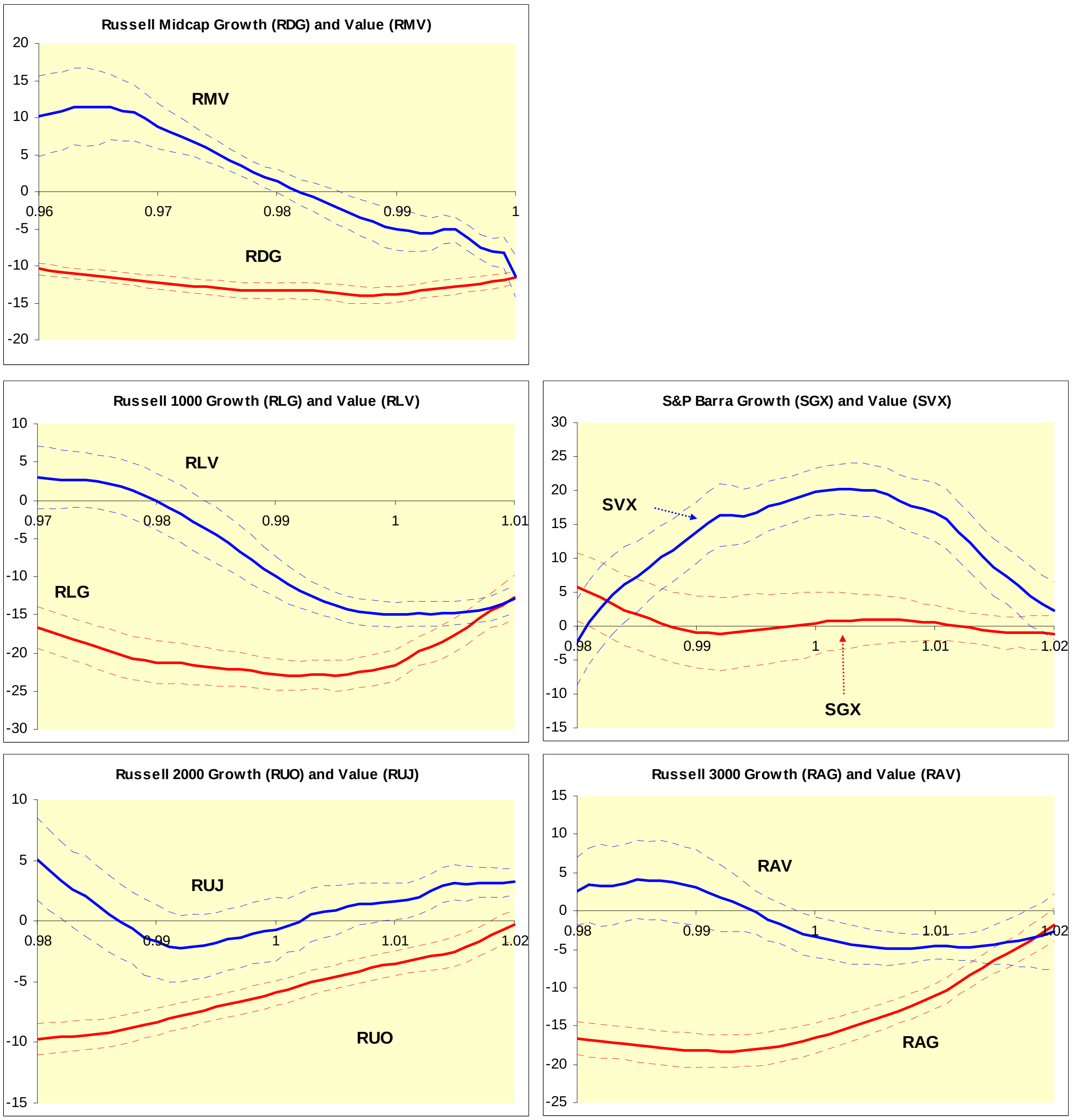

Table B1
Difference in Risk Aversion for Five Growth-Value Index Pairs

We use prices of options on five pairs of growth and value indices to estimate risk aversion across wealth, daily. The five index pairs are: Russell Midcap Growth (RDG) and Value (RMV) for December 2003—December 2004; The Standard & Poor's Barra Growth (SGX) and Value (SVX) indices for January 1996—December 1998; Russell 1000 Growth (RLG) and Value (RLV) indices for November 2003—December 2004; Russell 2000 Growth (RUO) and Value (RUJ) for December 2003—July 2005; Russell 3000 Growth (RAG) and Value (RAV) for December 2003—July 2005. A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from index options. True distribution is estimated using returns that are lagged by 6 months relative to the date when risk aversion is estimated. On each date we obtain risk aversion estimates for wealth levels ranging from 0.960 to 1.000 with step size of 0.001. Using the Satterthwaite difference in means test, which accounts for unequal variances, and the Brown-Mood non-parametric difference in medians test, we test if the mean and median risk aversions of the two representative agents are equal. We perform the test for each wealth level.

Wealth	Growth	Value	Satterthwaite Mean Test		Brown-Mood Median Test		Largest RA
	Mean	Mean	t-value	p-value	Z-value	p-value	
Panel A: Russell Midcap Growth (RDG) and Value (RMV) Indices							
0.960	-10.69	10.15	-20.98	<.0001	11.98	<.0001	Value
0.965	-11.65	11.36	-22.56	<.0001	10.89	<.0001	Value
0.970	-12.54	8.85	-30.03	<.0001	10.10	<.0001	Value
0.975	-13.31	5.14	-39.75	<.0001	8.55	<.0001	Value
0.980	-13.67	1.35	-30.34	<.0001	7.29	<.0001	Value
0.985	-13.87	-2.13	-14.33	<.0001	5.92	<.0001	Value
0.990	-13.93	-5.17	-8.19	<.0001	5.38	<.0001	Value
0.995	-12.85	-5.16	-6.79	0.0001	3.07	0.0011	Value
1.000	-11.64	-11.43	-0.05	0.9673	0.00	0.5000	Value
Panel B: S&P Barra Growth (SGX) and Value (SVX) Indices							
0.980	5.79	2.58	4.87	<.0001	-3.10	0.0010	Growth
0.985	1.70	10.14	-13.87	<.0001	5.28	<.0001	Value
0.990	-1.00	14.67	-27.84	<.0001	17.78	<.0001	Value
0.995	-0.49	18.85	-31.95	<.0001	19.07	<.0001	Value
1.000	0.43	18.79	-28.01	<.0001	16.57	<.0001	Value
1.005	0.96	17.23	-24.56	<.0001	14.62	<.0001	Value
1.010	0.53	14.84	-23.26	<.0001	14.96	<.0001	Value
1.015	-0.75	6.99	-13.11	<.0001	10.44	<.0001	Value
1.020	-1.13	1.44	-3.95	<.0001	4.30	<.0001	Value

Table B1—*Continued*

Wealth	Growth	Value	Satterthwaite Mean Test		Brown-Mood Median Test		Largest RA
	Mean	Mean	t-value	p-value	Z-value	p-value	
Panel C: Russell 1000 Growth (RLG) and Value (RLV) Indices							
0.970	-16.2	2.96	-32.74	<.0001	-19.47	<.0001	Value
0.975	-18.99	2.44	-39.55	<.0001	-21.17	<.0001	Value
0.980	-21.2	-0.17	-36.39	<.0001	-19.93	<.0001	Value
0.985	-22.05	-4.59	-31.31	<.0001	-17.73	<.0001	Value
0.990	-22.79	-10.09	-28.77	<.0001	-16.29	<.0001	Value
0.995	-22.89	-13.76	-26.12	<.0001	-17.09	<.0001	Value
1.000	-21.61	-14.98	-20.47	<.0001	-13.20	<.0001	Value
1.005	-17.58	-14.80	-8.40	<.0001	7.71	<.0001	Value
1.010	-12.65	-12.99	0.82	0.4137	-3.87	<.0001	Growth
Panel D: Russell 2000 Growth (RUO) and Value (RUJ) Indices							
0.980	-9.91	5.01	-20.46	<.0001	10.71	<.0001	Value
0.985	-9.40	1.27	-16.01	<.0001	10.05	<.0001	Value
0.990	-8.41	-1.67	-11.87	<.0001	8.88	<.0001	Value
0.995	-7.16	-1.77	-11.41	<.0001	7.16	<.0001	Value
1.000	-5.95	-0.61	-11.02	<.0001	8.09	<.0001	Value
1.005	-4.55	0.98	-13.94	<.0001	9.20	<.0001	Value
1.010	-3.39	1.74	-15.79	<.0001	9.46	<.0001	Value
1.015	-2.37	3.25	-16.77	<.0001	9.74	<.0001	Value
1.020	-0.24	3.30	-11.56	<.0001	7.57	<.0001	Value
Panel E: Russell 3000 Growth (RAG) and Value (RAV) Indices							
0.980	-16.46	2.56	-25.82	<.0001	15.17	<.0001	Value
0.985	-17.45	4.11	-25.37	<.0001	14.85	<.0001	Value
0.990	-18.25	3.09	-26.23	<.0001	13.85	<.0001	Value
0.995	-18.11	-0.22	-34.10	<.0001	13.91	<.0001	Value
1.000	-16.62	-3.45	-26.02	<.0001	12.85	<.0001	Value
1.005	-14.20	-4.76	-21.29	<.0001	11.44	<.0001	Value
1.010	-11.15	-4.53	-18.30	<.0001	11.56	<.0001	Value
1.015	-6.54	-4.39	-3.75	0.0003	3.73	<.0001	Value
1.020	-1.80	-2.73	0.79	0.4320	-1.31	0.0951	Growth

Table B2
Full-History Priors
Difference in Risk Aversion for Five Growth-Value Index Pairs

We use prices of options on five pairs of growth and value indices to estimate risk aversion across wealth, daily. The five index pairs are: Russell Midcap Growth (RDG) and Value (RMV) for December 2003—December 2004; The Standard & Poor's Barra Growth (SGX) and Value (SVX) indices for January 1996—December 1998; Russell 1000 Growth (RLG) and Value (RLV) indices for November 2003—December 2004; Russell 2000 Growth (RUO) and Value (RUJ) for December 2003—July 2005; Russell 3000 Growth (RAG) and Value (RAV) for December 2003—July 2005. A wealth level of one corresponds to zero return on the index. Risk-neutral probability distribution is obtained from index options. True distribution is estimated using returns on the Fama-French portfolio similar to the corresponding growth or value index. Full history of returns on the Fama-French portfolio is used, from 1926 until one month before the date when risk aversion is estimated. On each date we obtain risk aversion estimates for wealth levels ranging from 0.960 to 1.000 with step size of 0.001 (we use different wealth intervals for different index pairs depending on option data availability, but the step size is the same throughout). Using the Satterthwaite difference in means test, which accounts for unequal variances, and the Brown-Mood non-parametric difference in medians test, we test if the mean and median risk aversions of the two representative agents are equal. We perform the test for each wealth level.

Wealth	Growth	Value	Satterthwaite Mean Test		Brown-Mood Median Test		Largest RA
	Mean	Mean	t-value	p-value	Z-value	p-value	
Panel A: Russell Midcap Growth (RDG) and Value (RMV) Indices							
0.960	0.6593	2.0835	-1.84	0.0684	5.1114	<.0001	Value
0.965	-0.018	1.8154	-2.02	0.0464	5.3884	<.0001	Value
0.970	-1.482	4.2801	-8.83	<.0001	5.7310	<.0001	Value
0.975	-3.511	5.3388	-15.07	<.0001	9.3711	<.0001	Value
0.980	-5.207	4.5917	-14.38	<.0001	9.0277	<.0001	Value
0.985	-5.869	2.9597	-11.83	<.0001	8.0844	<.0001	Value
0.990	-5.844	2.5262	-11.82	<.0001	6.5588	<.0001	Value
0.995	-4.514	4.184	-12.75	<.0001	5.7911	<.0001	Value
1.000	-3.117	6.4229	-11.52	<.0001	4.8200	<.0001	Value
Panel B: S&P Barra Growth (SGX) and Value (SVX) Indices							
0.980	2.2228	1.1725	2.25	0.0249	2.5631	0.0052	Growth
0.985	-3.503	-0.445	-6.18	<.0001	5.0689	<.0001	Value
0.990	-7.869	-1.355	-13.16	<.0001	11.7043	<.0001	Value
0.995	-8.814	-1.146	-15.52	<.0001	12.9189	<.0001	Value
1.000	-7.507	0.5328	-16.62	<.0001	-13.4824	<.0001	Value
1.005	-5.216	2.2303	-17.11	<.0001	14.6133	<.0001	Value
1.010	-3.708	2.943	-15.95	<.0001	14.3233	<.0001	Value
1.015	-3.971	1.5194	-12.25	<.0001	10.6381	<.0001	Value
1.020	-4.227	-2.086	-4.01	<.0001	4.4362	<.0001	Value

Table B2—*Continued*

Wealth	Growth Mean	Value Mean	Satterthwaite Mean Test t-value	Satterthwaite Mean Test p-value	Brown-Mood Median Test Z-value	Brown-Mood Median Test p-value	Largest RA
Panel C: Russell 1000 Growth (RLG) and Value (RLV) Indices							
0.970	-3.894	6.7913	-16.19	<.0001	-13.3958	<.0001	Value
0.975	-8.526	6.5442	-23.63	<.0001	-16.5275	<.0001	Value
0.980	-12.86	3.895	-26.83	<.0001	-18.1079	<.0001	Value
0.985	-15.43	0.4025	-28.00	<.0001	-18.4810	<.0001	Value
0.990	-15.07	-3.341	-24.40	<.0001	-18.0453	<.0001	Value
0.995	-10.97	-3.929	-16.59	<.0001	15.0268	<.0001	Value
1.000	-5.112	-1.39	-9.51	<.0001	8.6431	<.0001	Value
1.005	0.8799	2.5126	-4.16	<.0001	2.5403	0.0055	Value
1.010	4.6524	6.0551	-2.65	0.0083	2.3617	0.0091	Value
Panel D: Russell 2000 Growth (RUO) and Value (RUJ) Indices							
0.980	1.1932	7.2213	-6.46	<.0001	7.2421	<.0001	Value
0.985	0.4374	3.8565	-4.68	<.0001	5.2998	<.0001	Value
0.990	0.1591	1.5988	-2.41	0.0183	1.4527	0.0732	Value
0.995	0.0153	0.1439	-0.32	0.7473	0.0256	0.4898	Val/Gro
1.000	-0.027	0.8086	-1.30	0.1993	0.5034	0.3073	Val/Gro
1.005	-0.009	2.6899	-3.61	0.0010	3.2478	0.0006	Value
1.010	-0.316	4.528	-3.79	0.0011	4.3250	<.0001	Value
1.015	-0.94	4.3115	-10.35	<.0001	3.5407	0.0002	Value
1.020	-1.064	2.0894	-6.30	0.0004	2.6788	0.0037	Value
Panel E: Russell 3000 Growth (RAG) and Value (RAV) Indices							
0.980	-7.743	3.9871	-16.69	<.0001	9.1789	<.0001	Value
0.985	-7.864	2.6496	-13.02	<.0001	7.8960	<.0001	Value
0.990	-7.884	1.5834	-13.33	<.0001	8.7243	<.0001	Value
0.995	-6.885	2.6418	-12.12	<.0001	7.0005	<.0001	Value
1.000	-5.356	6.8757	-11.18	<.0001	6.6778	<.0001	Value
1.005	-3.455	9.2299	-11.22	<.0001	6.1141	<.0001	Value
1.010	-1.987	11.665	-8.81	<.0001	5.3726	<.0001	Value
1.015	0.1555	12.937	-7.12	<.0001	5.1573	<.0001	Value
1.020	1.7998	13.75	-6.91	<.0001	5.1652	<.0001	Value