What Drives The Value Premium?

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Abstract

This paper shows that the value premium is largely concentrated in only 7% of the stock-market, when measured in terms of market capitalization. These stocks are those most held by individual investors. Also consistent with the predictions of behavioral explanations, the value premium monotonically decreases from 1.8% per month in the lowest institutional ownership decile to 0.1% in the highest institutional ownership decile. Risk-based explanations for this occurrence are found to be unsatisfactory; most notably, the three-factor model is strongly rejected. It is concluded that the value premium is a small and concentrated phenomenon that cannot be readily reconciled with the "rational" paradigm. Nonetheless, as far as market efficiency is concerned, most of the stock-market can be seen as "value anomaly free."

1. Introduction

Companies with a high book-to-market ratio (BEME), referred to as "value firms", have a higher return than companies with a low book-to-market ratio, or "growth firms". This "value premium" was first identified by Graham and Dodd (1934) and its interpretation has inspired heated debate. Some authors have warned that this finding may result from sample selection biases or data-snooping.[1] Its apparent persistence, however, both out of sample and after correction for selection biases, has lead to a near consensus on its authenticity. As a result, debate has focused on two central lines of argument. The first posits that a high BEME implies a higher discount rate. Advocates of this "rational" explanation propose various adaptations of the CAPM to capture the premium.[2] The second approach views BEME as a proxy for mispricing.[3] A combination of certain systematic errors made by investors with limited arbitrage constitutes the argument.

The fundamental idea in this paper is that if the value premium arises as a result of both pricing errors and limited arbitrage, then there should not be a value premium for stocks that are held by relatively sophisticated investors or for stocks that are inexpensive to arbitrage. Recently, extensive literature, which I detail and discuss in the next section, documents that institutional ownership (IO) reflects very well both sophistication and many relevant costs of arbitrage. As a result, IO provides a parsimonious way to classify stocks by their mispricing likelihood. If stocks held by institutional investors exhibit a significant value premium, then mispricing explanations will all be unsatisfactory as institutional investors are informed about the value premium and even if they were to make evaluation errors, the stocks they hold are liquid enough to enable arbitrageurs to remove any mispricing.

Graph 1

Consistent with both the IO-related literature and mispricing arguments, I find that the value premium (EHML) does monotonically decrease from a high 1.8% for low-IO stocks to a negligible 0.1% for high-IO stocks, as pictured in graph 1. This paper first investigates whether risk-based explanations can account for such evidence. Second, the concentration of the value premium, hence its economic importance, is measured and discussed. Third, a dynamic analysis is conducted to understand why the value premium is persistent.

To begin with, I study whether the three-factor model of Fama and French (1993) can capture this cross-sectional IO-EHML relationship and find that it does not for both equally-weighted and value-weighted portfolios. The risk-adjusted value premium decreases from 1.8% (low-IO) to -0.5% (high-IO). Moreover, the model is strongly rejected by Gibbons, Ross and Shanken's test (1987) and large pricing errors are generated – 0.28% per month on average – even when returns are value-weighted. Alternative risk adjustments, such as those proposed by Cahart (1997), Lettau and Ludvingston (2001), Ferguson and Shockley (2003), and the CAPM also generate high pricing errors and leave the IO-EHML relationship unexplained. Even the general risk argument, stating that a value premium should exist because the theoretical risk premium is contained in the denominator of BEME, as pointed out by Berk (1995), is at odds with evidence. Among mid and high IO stocks, there is no relationship between BEME and subsequent returns; a relationship that is very strong among low-IO stocks. Explanations based on liquidity are just as unsatisfactory as they do not explain why certain illiquid stocks (low-IO growth) underperform while other slightly more illiquid stocks (low-IO value) overperform. Furthermore, and as a consequence of the concentration of the value premium in low-IO stocks, when the bottom five IO-deciles are deleted, the value premium (both HML and EHML) decreases by more than one half and only 7% of the market capitalization is removed. The value premium is thus a small and concentrated phenomenon that is extremely difficult to reconcile with the "rational" paradigm. This extreme concentration of the value premium has very important consequences for both empirical and theoretical asset pricing research. These implications are detailed later in the paper but I will mention two of them here. First, studies that select a sub-sample of stocks that, for instance, either have at least two/five analysts following the stocks or are traded on the NYSE, end up with a sample that is almost value anomaly free. Such a fact is important to bear in mind when interpreting the results found in such samples. Second, the quality of asset pricing models is typically tested by how well the models capture the value effect. If the model intention is to provide a more accurate measure of, say, the cost of capital, then this model selection criterion may be misplaced. Indeed, what counts for such models is the dispersion of returns for the 93% of the market capitalization for which prices are determined by relatively sophisticated investors and for which arbitrage costs are low, rather than the other 7%; and these stocks do not exhibit a significant value effect.

Tests along the lines of Conrad, Cooper and Kaul (2002) are also performed and show that the reported IO-EHML relationship is unlikely to result from data-snooping. Furthermore, IO dominates size as a summary variable. Size has no marginal explanatory power over IO for detecting the stocks that drive the value premium. Among low-IO stocks, for example, it is the largest – not the smallest – stocks that exhibit the highest value premium (2.1%). In contrast, within any size-terciles, including the largest, low-IO stocks exhibit a high value premium.

The third task in this paper is to explain why the value premium is as high as its historical average over the last decade, i.e. why it is persistent. Indeed, this might cast doubt on the mispricing hypothesis, as we would expect sophisticated investors to learn or to arbitrage the anomaly away, or both. Nonetheless, and most importantly, a potential explanation for this persistence is the addition, over time, to the CRSP database of stocks that are both more prone to mispricing and very costly to arbitrage (e.g., small stocks with little disclosure requirements traded on the NASDAQ). This addition of stocks could very well mask the effect of learning from sophisticated investors or arbitrage activities, or both. To verify this explanation, I consider sets of stocks that are roughly time-homogenous from 1963 to 2001 (that is, either stocks traded on the NYSE or the largest 800 stocks). I then show that the value premium decreases over these 40 years in each time-homogenous sub-sample and has even disappeared over the last 15 years. Again, not only are these two pieces of evidence consistent with the mispricing hypothesis but explanations based on the rational paradigm are also hard to provide.

This paper complements two recent and independent papers that investigate the book-to-market effect. First, Ali, Hwang and Trombley (2003) find that long-run returns are positively and linearly related to the cross-effect between idiosyncratic volatility and BEME. However, consistent with the argument that IO is the best summary variable for mispricing with regards to the value premium, IO subsumes the effect of idiosyncratic volatility. Second, Nagel (2003) shares this finding, but claims that short-selling constraints are the main explanation for the existence of a value premium. I argue that short sales constraints cannot play a significant role in explaining the value premium as the puzzle concerns mostly the out-performance of value stocks.[4] The two papers also differ to that presented here as, in addition to methodological and sample selection differences, neither centers directly on the value premium. Indeed, they do not quantify the concentration of the value premium nor investigate the evolution of the value premium over time. In addition, little attention is paid to alternative risk explanations.

This paper then continues as follows: section two discusses the relationship between the mispricing hypothesis and institutional ownership. Section three lays out data selection schemes and descriptive statistics. Section four presents cross-sectional empirical findings and section five documents dynamic evidence. Section six provides robustness tests and section seven gives a brief summary and concludes.

2. Mispricing and the Value Premium

I begin here with a discussion of the mispricing hypothesis and the two building blocks on which it rests: the identification of the original errors that lead to mispricing and the limits to arbitrage that preserve it. The discussion then moves on to the choice of institutional ownership (IO) as a proxy for the cost of arbitrage, information availability, and investor sophistication.

2.1. The mispricing argument

As is extensively discussed in Barberis and Thaler (2002), Shleifer and Vishny (1997), and Shleifer (2000), any mispricing hypothesis involves two necessary conditions. First, there must be a reason for why prices have moved away from their intrinsic value. I will refer to this as ex-ante mispricing. Second, arbitrage activities should be costly in order for the anomaly to exist ex-post in the data. For the first necessary condition, the original and main mispricing argument explaining the value premium is established by Lakonishok, Shleifer and Vishny (1994). They argue that some investors, for various behavioral or institutional reasons, commit systematic errors when evaluating securities. Investors may overvalue growth stocks, being inclined to invest in firms that have a high current or future level of profit, regardless of the stock price. The opposite argument is used for value stocks as these may not appear attractive to investors. As a result, growth stocks are overvalued and value stocks are undervalued. LaPorta et al. (1997) test and cannot reject this hypothesis as they report a sizeable price correction around earnings announcements.[5]

Note that the above explanation is not the only one consistent with a return differential due to mispricing. Daniel, Hirshleifer and Subrahmanyam (2001) offer a pricing model in which risk-averse investors use their information incorrectly in forming their portfolios. In equilibrium, expected returns are linearly related to both risk and mispricing measures, such as

BEME. Behavioral models explaining return reversals (Daniel, Hirshleifer and Subrahmanyam, 1998, Barberis, Shleifer and Vishny, 1998, and Hong and Stein, 1999) also offer mispricing mechanisms that can lead to a value premium.

The second necessary condition of the mispricing hypothesis is that prices are only partially dragged down to their "correct" level by arbitrageurs who face costs in implementing arbitrage strategies. Barberis and Thaler (2002) review and discuss several impediments to arbitrage. A particularly relevant risk when arbitrageurs do not manage their own money but are rather the agents of several principals who provide funds, is noise trading risk, i.e. the risk that mispricing worsens in the short-run. In the event of low arbitrage returns, these principals may conclude that the agent is unskilled and terminate his contract. Moreover, both the long and short side can be very expensive or even impossible to setup. If arbitraging involves fixed costs, then one needs to trade a minimum number of shares in order for it to be profitable. However, sizeable trades are prohibitively expensive for certain stocks. In addition, certain stocks have very few shares available for borrowing; hence there are additional costs to implementing the short side.[6]

2.2. Institutional Ownership, Mispricing and Arbitrage

In this sub-section, I argue that institutional ownership (IO) is highly related to both the likelihood of having ex-ante mispricing and to the cost of arbitraging it away. Consequently, under the mispricing hypothesis, stocks with lower IO should exhibit a higher value premium.

All theories reviewed above describe some biases that are expected to be more severe among individual investors. As Lakonishok, Shleifer, and Vishny (1994) write: "Institutional investors should be somewhat freer from judgment biases and excitement about good companies than individuals." In addition, institutional investors dedicate considerable resources to data gathering and analysis, and sometimes enjoy privileged access to information concerning companies (selective disclosure). Institutional investors are thus likely to be more sophisticated and informed.[7] This claim is further supported by several recent empirical investigations. First, Bartov, Radhakrishnan, and Krinsky (2000) find lower post-earnings drifts for stocks with higher levels of IO. In addition, in explaining these drifts, they report that trading volume and size have little incremental power over IO. Second, Dennis and Weston (2001) find strong evidence that IO is positively related to a (microstructure-based) measure of informed trading. Third, Sias, Starks, and Titman (2002) argue that the price impact of institutional trading is important and results mainly from the information content of their trades. Finally, several studies reveal that the stocks institutional investors purchase subsequently outperform those they sell; see among others Daniel et al. (1997), Nofsinger and Sias (1999), Wermers (2000), and Chen, Hong, and Stein (2002).

Another common corollary of behavioral theories is that mispricing should be corrected more quickly among stocks that have widely available information on fundamentals. LaPorta et al. (1997) state that: “results for firms larger than the NYSE median are weaker, which may be due to a tendency of widely-followed stocks to adjust to news more continuously”. As shown in the descriptive statistics (see next section), IO is strongly correlated with the number of analysts following a stock. In addition, Sias and Starks (1997) provide evidence consistent with the hypothesis that institutional trading increases the speed at which prices reflect information. The evidence about earning announcements (Bartov et al., 2000) is also consistent with this claim.

The second building block of the mispricing hypothesis relates to arbitrage limits. Both noise trading risk and implementation costs are expected to be higher for low-IO stocks. First, noise trading is often seen as resulting from the trades of individual investors; see De Long et al. (1990). Second, the main implementation cost for arbitrageurs to consider is the price impact of their trades. If the stocks to be arbitraged are illiquid, the total profit from arbitrage may be too small to cover both the fixed costs and the risk of arbitrage activities. The question then is how liquidity relates to IO. A first answer is given by Glosten and Milgrom (1985), who argue that one cause of illiquidity is the presence of privately informed investors. Consequently, high-IO stocks should be less liquid, and not more liquid. This apparently counter-intuitive result is clarified by Sarin, Shastri and Shastri (2000). They find that the quoted bid-ask spread is indeed negatively related to IO, but, interestingly, the quoted depth is strongly *positively* related to IO. Hence, taking a sizeable position in low-IO stocks is likely to be more costly overall. This claim is also consistent with Gompers and Metrick (2001), who find a strong positive relationship between IO and two proxies for liquidity (price level and turnover), even after controlling for size. Moreover, in the next section, I show that IO is very strongly negatively related to the illiquidity ratio of Amihud (2002), a proxy for price impact. Consequently, these results indicate that transaction costs faced by arbitrageurs are significantly higher for low-IO stocks.

Another cost to consider when arbitraging the value premium is the cost of short-selling. To begin with, note that individual investors very rarely lend their shares, either directly or indirectly, and that all outstanding shares are not necessarily floated as insiders may hold, but do not trade (nor lend), their shares. In line with this argument, D'Avolio (2002) reports that IO is the main explanatory variable for the quantity of shares supplied. Once IO is accounted for, variables such as size, BEME, and turnover have a negligible marginal explanatory power. He also reports that loan fees are higher for low-IO stocks. In addition, as high-IO stocks have a higher quantity of shares available for borrowing, arbitrageurs are expected to face both lower bargaining costs and lower search costs when borrowing shares of high-IO stocks.[8] Finally, derivative instruments, which are an alternative way of taking short positions, are likely to be available and liquid for institutionally held stocks.

Costs of arbitrage, initial pricing errors, and the sluggish incorporation of information into prices, are thus inversely related to IO in a consistent way.[9] The fact that IO captures all of these dimensions at once is a force and not a drawback. Baker and Wurgler (2003, p7) state that "in practice, the same stocks that are hardest to arbitrage are also most vulnerable to sentiment (...) while this makes the channels themselves difficult to distinguish empirically, it makes it easier to derive robust empirical predictions." This is precisely why IO is a very good variable in the present context. I would even go further and argue that studying the effect of arbitrage costs in isolation to mispricing is not only difficult but also meaningless. Indeed, if stocks are held by sophisticated investors who price them right to begin with, then arbitrage costs such as idiosyncratic volatility are irrelevant to detect ex-post mispricing. A direct proxy for arbitrage cost is thus likely to be less related to the magnitude of the value premium than IO.

The above discussion thus leads to the following (cross-sectional) claim:[10]

Ca: A decreasing relationship should exist between IO and the value premium.

Furthermore, as investors are expected to learn over time about pricing errors, in particular after the extensive documentation of the value premium, both in academic and popular articles, the value premium should weaken over time. In addition, as Hirshleifer (2001) states: "the rise of arbitrage based upon modern statistical analysis (...) will indeed reduce mispricing." Also, both institutional ownership and analyst coverage have increased over time (Gompers and Metrick, 2001, and Hong, Lim, and Stein, 2000). These observations put together lead to the following (time-series) claim:

Cb: In a time-homogenous set of stocks, the value premium should decrease over time.

3. Data and Summary Statistics

Data on analyst coverage are taken from the I/B/E/S Historical Summary File, those on accounting and market performance are collected through the CRSP-COMPUSTAT Merged Database. I also take the complementing accounting data provided by Davis, Fama, and French (2000), that are based on *Moody's Industrial Manuals*.[11] Only common and non-financial stocks are included. Delisting returns are taken into account as proposed by Shumway (1997). The book value of equity (BE) is computed as the book value of equity (COMPUSTAT Data Item, C.D.I 60), plus deferred taxes (C.D.I. 74) and investment tax credits (C.D.I 208), minus the book value of preferred stock (C.D.I 56, 10, or 130, in that order). From July of year *t* to June of year *t*+1, the book-to-market ratio is $BEME_t = BE_{t-1}/ME_{t-1}$, where ME_{t-1} (BE_{t-1}) is the market (*book*) value of equity at the end of year *t*-1. Negative values of BEME are discarded, and in order to reduce selection biases, information about BE_{t-2} is required. I also construct the time-series of stock illiquidity ratios proposed by Amihud (2002). This illiquidity ratio can be interpreted as the price impact per $1 million traded in a day, expressed in percentage terms. To construct this, I average, over a year, the (daily) ratios of the daily absolute return to the dollar trading volume (in million) on that day. Idiosyncratic volatility is constructed as in Ali et al. (2003). It is denoted Ivol and is obtained by regressing daily returns on the CRSP value-weighted index over a maximum of 250 days ending on June of year *t*, and then computing the variance of the residuals. Finally, dividend yields are constructed as in Grinstein and Michaely (2002). For each month of year *t*, the dividend yield for a given firm is set to be four times the last quarterly dividend paid in year *t*-1 divided by ME_{t-1}.

The value premium is computed using two alternative methods. The first method consists of taking the difference between the average (equally weighted) return of the 25% of stocks with the highest BEME (value stocks) and the 25% of stocks with the lowest BEME (growth stocks). This measure is denoted EHML. The second method follows Fama and French (1993, 1996) and is denoted HML.

Data about institutional ownership (IO) from 1980 to 2001 are constructed from the CDA/Spectrum 13F database. These data come primarily from the SEC 13F form in which institutional investment managers with over $100 million of securities under discretionary management must report their quarterly common-stock positions that are either above 10,000 shares or $200,000. Positions below 10,000 shares and worth less than $200,000 may be also disclosed on a discretionary basis. These institutional investors mainly consist of banks, insurance companies, mutual funds, large brokerage firms, pension funds, and endowments. Gompers and Metrick (2001) provide a detailed analysis of this database and I follow their methodology in constructing institutional ownership (IO). This is defined as the fraction of a company's shares that are owned by institutions filing the 13F form. These data are noisy as a result of the way CDA/Spectrum handles late fillings and the fact that small positions in a stock do not have to be disclosed. Late filing is rare (4% of the observations) but is concentrated in small stocks. I, therefore, include these holdings and adjust the reported number of shares should a stock split have occurred. The proportion of observations with IO reported at zero decreases steadily from 20% in December 1980 to less than 1% in December 2001. Note that whenever I form IO-deciles, zero-IO observations are excluded to enable the computations. Otherwise, zero-IO stocks are included as such.

Table 1

As this paper focuses on the interaction between Institutional Ownership (IO) and the value premium, it is very important to have a comprehensive picture of what characterizes both low-IO and high-IO stocks. Table 1 provides an overview of sub-samples formed using IO. All stocks that satisfy the above criteria are included and all averages weigh equally each of the 258 months (7/1980-12/2001).[12]

First, as reported in the literature, institutional ownership varies dramatically, from 1% in the lowest IO-decile to 68% in the top IO-decile. Second, institutional investors own portfolios that are tilted toward stocks that are large, mature, growth, winners (high past returns), less levered, offer higher dividend yields (DY), are widely followed by analysts, have lower idiosyncratic volatility, and are more liquid.[13]

Grinstein and Michaely (2002) investigate the relationship between IO and DY and conclude that institutional investors prefer stocks that pay a low but strictly positive dividend. The increasing average dividend yield, which is observed in Table 1, reflects, therefore, a decreasing proportion of stocks that do not pay dividends as one moves toward higher IO-deciles.[14] Past returns also vary substantially across IO-deciles. Value stocks and low-IO growth stocks have a similar past performance, whereas high-IO growth stocks tend to be strong winners (+109% over the past 24 months). This is an important fact as all growth stocks are often thought to be past winners. Even though this assertion is correct overall, it holds mainly for high-IO stocks.

Consistent with the mispricing hypothesis and the discussion in the previous section, the spread in BEME decreases with IO. This can be interpreted as a sign that extreme valuations are anomalous, and are thereby concentrated in low-IO stocks. In the lowest IO-decile, value (*growth*) firms have an average BEME of 2.1 (*0.1*), whereas in the highest IO-decile value (*growth*) firms have an average BEME of 1.3 (*0.2*). The fact that there is more spread in BEME among low-IO stocks is an important characteristic. It implies that risk-based explanations that view BEME as being related to the discount rate would predict a stronger value premium among low-IO stocks, which is the claim Ca. This point will be covered at length in section 6.4.

Given the discussion in section 2, it is important to analyze the relationship between IO and the number of analysts following the stock (NAF), idiosyncratic volatility (Ivol), and illiquidity

(ILLIQ). Descriptive statistics in Table 1 shows that, as claimed in section 2, these relationships are very strong. Indeed, NAF increases from less than 1 for low-IO stocks (both value and growth) to 13 for value high-IO stocks and 9 for growth high-IO stocks. Ivol and ILLIQ decrease monotonically with IO. Low-IO stocks have very high trading costs (5.1% for value stocks and 2.6% for growth stocks) while high-IO stocks have very low trading costs (0.2% for value stocks and 0.1% for growth stocks).[15] Interestingly, inside each IO-decile, value stocks appear to be significantly less liquid than growth stocks. This fact may then explain part of the value premium exhibited by low-IO stocks, providing that liquidity is priced. This possibility is investigated in sub-section 4.4.

Table 2

Table 2 – Panel A reports the transition matrix for IO at a yearly frequency.[16] A key fact that emerges is the strong persistence of IO. A firm from any decile at June end of year *t* remains in this same decile at June end of year *t*+1 in more than one third of the cases. This figure even reaches 60% and 67% for the lowest and highest IO-deciles. In addition, it is rare that stocks move up or down by two deciles or more over a year. The maximum observed is 7.5% (moves from decile 5 to 3). Another important fact is that the number of stocks that are removed from the sample from one year to the other decreases with IO. In the lowest IO-deciles, as much as one quarter of the stocks is excluded the following year, either because they have zero-IO reported at this time or because they are delisted.[17]

Table 2 – Panel B documents the persistence of value and growth classification within each IO-decile. From this matrix, it can be deduced that an investor pursuing a value strategy in the lowest IO-decile (exclusively) would have to rebalance 60% of the portfolio every year. In addition, stocks moving from growth to value and vice versa are very rare (2.3% maximum).

Knowing the persistence of IO and BEME is of interest for several reasons. First, it shows that information about IO and BEME is "long-lived", which is important when considering market efficiency issues and also when assessing the transaction costs involved in the implementation of a value strategy conditional on IO. Second, persistence justifies the interpolation for some zero-IO observations. Indeed, if an IO is zero in a given quarter and IO is positive both before and after that quarter, then this observation is likely to be invalid. Third, as mentioned in section 2, this simplifies the study design as results change very little when one uses lagged IO levels.

4. Cross-Sectional Analysis

This section documents the (cross-sectional) relationship between Institutional Ownership (IO) and the value premium for raw returns, as well as both size and risk-adjusted returns. The robustness of the negative impact of IO on the value premium is then shown via a multiple regression, which also includes the marginal contribution of size, liquidity, analyst coverage, and idiosyncratic volatility.

4.1. The Value Premium and Institutional Ownership

In this sub-section, I focus on raw returns and investigate the claim Ca. This claim states that a decreasing relationship should exist between IO and the value premium. At the beginning of each quarter, IO-deciles are formed. Within each decile, I compute the difference between the average return of value and growth stocks for each of the following three months. The resulting time-series of monthly returns is denoted EHML. Results are displayed in Table 3-Panel A.

Table 3

The regularity of the relationship between EHML and IO is striking. EHML monotonically decreases from an extremely high 1.8% per month (*t*-statistic = 4.1) for stocks in the lowest IO-decile to a negligible 0.1% per month (*t*-statistic = 0.2) for stocks belonging to the highest IO-decile. Given the discussion in section 2, and if one believes that there is no arbitrage opportunities, this monotonicity may be interpreted as the marginal cost faced by arbitrageurs in equilibrium. Such a large cost of arbitrage for low-IO stocks is not surprising given both the illiquidity and the lack of analyst coverage for these stocks; see Table 1. No less striking, moreover, is the magnitude of the premium and the extreme performance of both growth and value stocks. As a benchmark, over the same period, the S&P500 has averaged 1% per month and the risk free rate 0.5%. Growth stocks in the five bottom IO-deciles, therefore, earn about the risk free rate. Value stocks, on the other hand, earn a return as high as 2.5% in the lowest IO-decile and display a clear out-performance only in the bottom 4 deciles. Overall, the value premium is seen to jump at about the median stock. That is, while the value premium is high and statistically significant from decile 1 to 5, for decile 6 to 10, the value premium is low and no longer statistically significant. In addition, from Table 1, one can deduce that these highest 5 deciles represent over 93% of the entire market capitalization. This is, therefore, a first indication of the extreme magnitude and concentration of the value premium.

In Panel B and Panel C, I show the robustness of the monotone relationship between IO and the value premium. First, carrying out an independent sorting instead of a dependent sorting does not change results. In fact, it makes the relationship slightly stronger. Second, including stocks with an IO reported at zero and then creating quintiles (as 20% of the stocks have zero IO in the first months of the sample), leaves the monotonicity and strength of the relationship unaffected. The value premium is 1.65% in the lowest IO-quintile and 0.09% in the highest IO-quintile.

These results also give a sense of the relative contribution of the long side (value) and short side (growth) to the value premium. In the lowest IO-decile, for example, value stocks outperform (the S&P 500) by 1.4%, while growth stocks underperform by 0.4%. The total value premium is, therefore, made up of 22% coming from the short side and 78% coming from the long side. Overall, from 1980 to 2001, the value premium is 1% (see Table 7) and value stocks have an average performance of 1.85% versus 0.85% for growth stocks (non-tabulated results). As the S&P500 is relatively inexpensive to sell short, an arbitrageur who cannot sell short any low-IO growth stocks, can short the S&P500, and obtain a return of 0.85% on a zero-cost portfolio, which constitutes 85% of the overall value premium. The inability to sell short low-IO stocks then eliminates only 15% of the overall value premium. However, these figures are based on raw returns so one may wonder what happens after risk correction. In Table 4 and Table 8, abnormal returns from various asset pricing models are displayed and it is apparent that growth stocks underperform, but much less than value stocks outperform; with a few exceptions however. This confirms the above assertion that we are dealing with a value premium puzzle and not a growth discount puzzle. Of course, adjusting for risk in this context is a delicate issue as all risk models are rejected in turn. It is, therefore, not so clear as to whether one might trust better evidence based on raw returns rather than evidence based on wrongly risk-adjusted returns.

The fact that the value premium is so high among low-IO stocks is certainly difficult to explain in terms of risk compensation. No less puzzling is the fact that there is *no* value premium among high-IO stocks.[18] Table 3, therefore, contains two equally strong and puzzling pieces of evidence for asset pricing theory: a very high value premium among low-IO stocks and no value premium among high-IO stocks.

Note that a similar analysis is performed in Ali et al. (2003). They present the 36-month return difference between value and growth stocks in deciles based on idiosyncratic volatility (Ivol), Price, Volume, IO, market cap. (ME), etc. The relationship between the value premium and each characteristic is never monotone and the largest spread (between the value premium of the top and bottom decile) is obtained for Ivol and IO. This suggests that the monotonicity that I uncover may not hold for long-run returns over the sub-period 1987-1997. However, as this paper focuses on the driver of the value premium, I am interested only in 1 to 12 month returns, as do Fama and French (1993). In addition, as seen in Figure 2 in Ali et al. (2003), in the year after portfolio formation the value premium is similar for high and low Ivol portfolios, which indicates that Ivol may have less relevance for the value premium than claimed by these authors. This issue is discussed further in sub-section 4.4.

4.2. Adjusting For Distress Risk

In this sub-section, I investigate whether the distress risk explanation, suggested by Fama and French (1993), is consistent with the above evidence. Let me here mention three potential channels. First, institutions bias their holdings toward firms with high external validation; see section 3. It is then possible that institutional investors avoid firms with a high risk of distress despite substantial compensation. Second, public authorities may be more inclined to rescue a firm from bankruptcy when the firm is large and held by institutional investors. This could, potentially, be so as to avoid a financial crisis. Third, and finally, Fama and French (1996) postulate that a value premium exists because distress risk is strongly correlated across firms, making the human capital wealth of individual investors co-moves positively with the economy-wide distress risk. Potentially, institutional investors are more reluctant to hold stocks that have a high exposure to economy-wide distress risk. Consequently, it would be among stocks held by individual investors that the value premium would be strongest. To test these conjectures, returns are adjusted with the three-factor model of Fama and French (1993).

Within each IO decile, stocks are separated into low BEME (bottom 25%, value), intermediate BEME, and high BEME (top 25%, growth), resulting in thirty portfolios sorted by IO and BEME. I then run independent time-series regressions of the portfolio excess returns on the factors and obtain abnormal returns (i.e., alphas) of the value and growth stocks for each IO-decile, as in Fama and French (1993). Results are reported in Table 4.

Table 4

After this risk adjustment, low-IO growth stocks do not underperform significantly while low-IO value stocks outperform significantly – alpha is as much as 1.3% per month for the lowest-IO value stocks. Most importantly, the relationship between the value premium and IO is virtually identical to that reported in Table 3 with raw returns. The value premium is estimated to be about 2% for low-IO stocks and slightly negative for high IO-stocks.

It is also interesting to measure how well the model captures the dispersion of returns, especially if one thinks of IO-BEME portfolios as representing a wider dispersion of returns than the widely used size-BEME portfolios. To measure the goodness-of-fit of the model, I report the average pricing errors across the 30 portfolios in order to evaluate their economic significance. I also compute the *F*-test of Gibbons, Ross, and Shanken (1989), GRS hereafter, to statistically test the null that all the "alphas", i.e. the thirty intercepts, are jointly zero.

The GRS statistic has a very low p-value (about 10^{-5}). This very strong rejection of the three-factor model may not be surprising (although the magnitude of the rejection certainly is) as Fama and French (1996) report that the GRS test rejects the hypothesis that the three-factor model explains the average returns on their 25 size-BEME portfolios at the 0.4% level. They argue, however, that "this rejection is testimony to the explanatory power of the regressions (…) The model does capture most of the variation in the average returns on the portfolios, as witnessed by the small average absolute intercept, 0.09%." Judging whether the absolute intercept is large or not is subjective. The GRS statistic, in contrast, is a more objective measure of the success of a model, and on these grounds, the model is clearly rejected. In addition, when confronted with IO-BEME portfolios, the average absolute intercept appears high by any standards. It reaches 0.28% per month, three times as much as with the 25 size-BEME portfolios.[19] Not only does this result show that the relationship between IO and the value premium cannot be explained by the three-factor model, but it has important implications for asset pricing theory as a whole as the widely used three-factor model is strongly rejected when confronted with IO-BEME portfolios.

4.3. Size versus Institutional Ownership

In this sub-section, I verify that IO dominates size as a summary variable, in line with the argumentation in section 2.[20] Terciles based on IO (*size*), and within each of these, terciles based on size (*IO*) are created. Table 5 shows that, within each size tercile, the value premium decreases dramatically with IO, testimony of a strong marginal effect of IO. Small stocks with a high-IO do not exhibit a significant value premium even though they are very small ($22 million on average). Intermediate size stocks that are substantially bigger but have a low IO, in contrast, have a value premium as high as 1.9% per month and have a market capitalization of $82 million on average. The domination of the IO effect is even clearer when I perform the reverse operation, i.e. rank first by IO then by size. The value premium in the low-IO stocks is actually concentrated in the largest stocks ($154 million on average) for which it reaches a staggering 2.1% per month. Among the other IO-terciles, the value premium is smaller and similar across size sub-samples, despite wide variations in market capitalization. In conclusion, size has no marginal explanatory power over ownership in explaining the performance of growth versus value stocks, and appears to be a noisy proxy for IO.

In Table 5, it is also interesting to note that, among mid-cap stocks, low-IO growth stocks do very poorly. Similarly, among low-IO stocks, both mid-cap growth stocks and large-cap growth stocks do very poorly also. This explains why Nagel (2004) finds that the value premium is driven by the underperformance of growth stocks. His sample excludes small-cap and he constructs a size-adjusted IO measure. He then finds, consistent with the evidence in this table, that the growth stocks which, given their size, have a low IO do very poorly. Three points are worth noting here. First, size is not a measure of risk. Hence, to know if growth stocks underperform more than value stocks outperform, one should use an explicit asset pricing model. This is done in Table 4 and Table 8, and most asset pricing models indicate that value stocks are more anomalous. Second, this does not mean that size should be neglected. It is known that the value premium is higher among small stocks, hence it is important to verify that the IO effect documented in this paper is the dominant effect and this is what is done in this sub-section. Third, most of the analysis in this paper is conducted with IO-sorted stocks and not size-adjusted IO sorted stocks because all evidence reviewed in section 2 concerns the level of IO of a given firm, and not firms with an abnormally high or low level of IO.

Table 5

This approach has the benefit of offering economic magnitudes and leads to unambiguous results. When comparing IO to other variables such as idiosyncratic volatility (Ivol), liquidity (ILLIQ) or analyst coverage (NAF), the above methodology is less conclusive and a multiple regression approach is required. In addition, the regression approach enables me to control for various characteristics that influence returns. The drawback of using such an approach is that it no longer focuses on the value premium but rather on the book-to-market effect, that is, a linear relationship between returns and the natural logarithm of BEME. The two are not equivalent but are nonetheless closely related.

4.4. Regression analysis

In this sub-section, I regress returns on various characteristics, including several cross-effects: BEMExSize, BEMExIO, BEMExILLIQ, BEMExNAF, and BEMExIvol. These regressions are run independently from one another every quarter. The time-series averages of the coefficient estimates are displayed in Table 6. The t-statistics are computed in the usual Fama-MacBeth fashion and are adjusted for autocorrelation using the Newey-West method. Certain variables (BEME, size, Ivol, ILLIQ and NAF) display extreme skewness, hence I take a natural logarithm transformation. Then, to facilitate the interpretation of the coefficients, all variables are demeaned and standardized (i.e., expressed as a z-score).

Table 6

As predicted in the discussion in section 2, panel A shows that the book-to-market effect is stronger for stocks with high idiosyncratic volatility, stocks followed by few analysts, small stocks, and stocks that are held mainly by individual investors. Also consistent with the arguments made in section 2, when IO is compared to each of these characteristics (panel B), IO always dominates.[21] This is consistent with the interpretation of IO as a summary variable which captures these three dimensions (NAF, ILLIQ, and Ivol) in addition to sophistication and other relevant costs of arbitrage in a consistent way. This result is also important in light of Griffin and Lemmon (2002) and Ali et al. (2003), who show, respectively, the importance of analyst coverage and idiosyncratic volatility for the magnitude of the value premium.

Despite the fact that the value premium is not about a linear relationship between BEME and returns, these regressions enable to test the marginal explanatory power of IO, holding many characteristics constant and also provide a useful robustness check for the analysis conducted in sub-section 4.1 and 4.3. In addition, it shows that controlling for liquidity does not affect my results. This was expected as it is difficult to explain why certain illiquid stocks (low-IO growth) underperform while other slightly more illiquid stocks (low-IO value) outperform significantly, based on liquidity considerations. This is to say that the puzzle centers on why among similarly illiquid stocks, certain stocks have abnormally high performance and certain stocks have an abnormally low performance. Hence, taking into account liquidity does not help to explain the puzzle.

5. Dynamic Analysis

As proposed in section 2, the mispricing argument implies that in a time-homogenous set of stocks, the value premium decreases over time (claim Cb), while risk-based explanations would be, a priori, at odds with such evidence. Time heterogeneity refers to the fact that smaller and smaller stocks have been added to the CRSP database over time, making the cross-section of stocks time-heterogeneous. Potentially, this can confound inferences, as arbitrage may successfully decrease mispricing but the addition of even more challenging stocks might give the impression that mispricing is, overall, persistent and thus unchallenged.[22]

In order to assess the claim Cb, I report, in Table 7-Panel A, the change in the value premium for two time-heterogeneous and two time-homogenous samples. The objective is to compare the evolution of the value premium for the two types of sample. The first (time-homogenous) sample, denoted "All common", is the time-series of HML that is widely used in empirical research (available from Kenneth French's website). It comprises all common stocks, including financial firms.[23] The second sub-sample, denoted "All (-fi,-pb)" is like "All common" but excludes financial firms and those for which there is no data on their BE in the previous year. The two (roughly) time-homogenous sets of stocks are "Top-800", corresponding to the 800 largest stocks as of June *t*, and "NYSE", corresponding to the stocks listed on the NYSE as of June *t.* As data are available starting in July 1964 for these samples, I display results for three periods of equal length: 7/1964-12/1976, 01/1977-06/1989 and 07/1989-12/2001. Note that when I compute HML on a sub-sample, I strictly follow the methodology of Fama and French (FF, 1993). For example, for the "Top-800", I first determine the breakpoints based on those that are traded on the NYSE (and belong to the "Top-800") then value-weight and average portfolio returns in the manner described by FF. The breakpoints are thus never the same across sub-samples.

I test the hypothesis that the average value premium is equal in the first and last time-periods using both the standard difference-in-means *t*-test and the non-parametric Wilcoxon ranked-sum test.[24] In the time-heterogeneous samples, there is no evidence of a decrease in the value premium. For example, EHML for all common stocks is actually slightly higher in the third period (0.84%) than in the first period (0.78%).[25] In contrast, for time-homogenous samples, the decrease in value premium is substantial. EHML for NYSE stocks decreases from 0.68% to 0.15% and EHML for Top-800 stocks decreases from 0.78% to -0.09%. Similarly, HML for NYSE stocks decreases from 0.53% to 0.04% and HML for Top-800 stocks from 0.61% to -0.18%. The economic magnitude of the drop is, thus, considerable. Nonetheless, volatility is high, hence statistical tests are somehow weak. The hypothesis of an equal mean is, nonetheless, always rejected at a 10% level test; except for the NYSE sample when the value premium is measured by EHML. In addition, one point is worth emphasizing. One might think that the observation of a weak value premium in recent years is only to be expected as the late 90s experienced an extraordinary "tech-bubble" that is unlikely to reoccur. One should bear in mind, however, that the value premium for the entire sample in the 90s is no lower than in previous years, whether measured by HML or by EHML. The phenomenon documented here is, therefore, not the artifact of a rare event taking place but is part of a trend seen in a very specific set of stocks. This said, I cannot reject the rational paradigm based on this evidence, but it is certainly consistent with claim Cb and offers one additional stylized fact that challenges risk-based explanations of the value premium.

Table 7

In Panel B, I quantify the concentration of the value premium. The analysis is carried out from July 1980 to December 2001 (P0), due to data availability restrictions for IO. This time period is also divided into three sub-periods of 86 months (P4, P5 and P6) in order to provide evidence on the evolution of the concentration of the value premium. The overall concentration is about the same whether one looks at HML or EHML. Basically, more than half of the overall value premium is removed when only the top 50% IO stocks are kept, that is half of the stocks with the highest level of institutional ownership. EHML decreases from 1% to 0.4% and HML from 0.3% to 0.1%. Of particular interest, this sub-sample represents as much as 93% of the overall market capitalization. Hence, more than half of the value premium is driven by the 7% of the market capitalization that is most held by individual investors. In addition, this extreme concentration has increased over time. Over the last 14 years, it is most, if not all, of the value premium that is driven by this 7% of the universe. For example, in the last sub-period, in the top 50% IO stocks, HML is negative on average and EHML averages 0.14% only. In comparison, HML (*EHML*) averages 0.31% (*0.93%*) in the sample "All common".

Panel B also confirms the economic significance of the decrease of the value premium for time homogenous sets of stocks. From the first (P4) to the third sub-period (P6), EHML for NYSE stocks is divided by 5 and it is divided by 6 for "Top 50% IO" stocks. While, over the last 7 years, the HML posted by Kenneth French averages 0.33% per month, close to the long-run average, HML is close to zero or negative for NYSE, Top-800, and Top 50% IO stocks. This is further indication that the value premium is disappearing wherever arbitrage costs are moderate. It also suggests that, in the future, if smaller stocks get added at a slower pace and/or arbitrage costs decrease then the value premium could disappear completely.

Table 7 also sheds lights on a debate initiated by Loughran (1997), who points out that there is no book-to-market effect for big stocks. That is, among big stocks, returns are not linearly related to BEME. He then claims that the value premium is not economically relevant. In response, Davis, Fama, and French (2000) state that, unlike what linear regressions suggest, HML for big stocks is 0.3% per month from 7/1963 to 6/1997, which is economically relevant. In contrast, I show that if one eliminates the really anomalous stocks, i.e. one focuses on high-IO stocks and not simply on big stocks, HML is not even economically relevant for most of the stock-market universe. Another argument put forth by Davis et al. (2000) is that, prior to 1963, both small and big stocks had a similar value premium. It is, however, worth noting that prior to 1963 there were fewer stocks present in the CRSP database and that these stocks shared similar characteristics. It may, therefore, not be surprising to find a similar value premium among both small and big stocks in this sample.

6. Further Analysis

The above analysis may be subjected to four critiques raised recently in the literature. First, the double-sort procedure that I use can generate extreme returns; see Conrad, Cooper, and Kaul (2002). Second, certain models have been shown to capture the value premium as well as the three-factor of Fama and French (1993). Third, the omission of leverage may explain the IO-EHML relationship. Fourth, there is more dispersion in BEME for low-IO stocks than for high-IO stocks, hence a general risk argument is not rejected. Finally, I discuss the extension of this approach to the momentum phenomenon.

6.1. Data snooping

A Monte-Carlo simulation is used to assess the likelihood of data-snooping biases in my choice of institutional ownership and its consequence. Data-snooping arises when one ignores, in his statistical inference, the fact that many searches have been conducted in order to obtain the final specification. In this paper, such a bias would arise had I looked at many characteristics and reported results for which that worked best. In this instance, t-statistics should be appropriately corrected. For example, if one obtains a t-statistics equal to 3 for the test of $r = 0$, then the likelihood that r is not zero is about 99.9% (assuming normal distribution). Nonetheless, if a hundred tries have been made and the highest t-statistics is reported, then the likelihood that r is not zero is below 90%. Caution is, therefore, required when interpreting the evidence in table 3, in particular the t-statistics.

In support of my position, however, I argue that even if IO has been motivated empirically, the range of choice to proxy for the cost of arbitrage and sophistication is small and IO appears to be the most suitable option, as discussed in section 2. In addition, in order to gauge how exceptional it really is to obtain a strictly decreasing relationship between EHML and IO, and to obtain an EHML of about 0% for high-IO stocks and as high as 1.8% for low-IO stocks, I simulate a characteristic that plays the role of IO, in the spirit of Conrad, Cooper, and Kaul (2002). The analysis performed in sub-section 4.1 is repeated by simply replacing the matrix of IO (real one) with a matrix of simulated-IO. A hundred rounds are run. For each round, I generate 25 matrices of simulated-IO. The output is thus 25 series of 10 EHML, one for each simulated-IO-decile. Three series are kept (they may be the same). The first series contains the highest generated EHML across deciles. The second series contains the lowest generated EHML across deciles. The third and last series has the largest spread between the EHML of the lowest simulated-IO-decile and the highest simulated-IO-decile. In addition, I check how many monotonic relationships are generated. Furthermore, this analysis (i.e., the 100 rounds) is run for two different types of simulated-IO. The first type is simply randomly generated. It is a matrix of independent drawns from a normal distribution. The second type is generated by taking the difference between a number drawn from a standard normal distribution and the absolute value of the difference between BEME and its cross-sectional mean (dBEME). This simulated-IO has a higher coefficient of correlation with dBEME than the real IO. This aims to address the remark of Conrad et al. (2002), stating that when a double sorting device is used, and the two sorting characteristics are correlated, the standard t-statistics may be greatly misleading.

Results, reported in Table 3 – Panel B, confirm this statement. When the simulated characteristic is correlated with the dispersion in BEME (dBEME), a value premium of the order of 1.8% is common for the bottom IO-deciles. In contrast, such magnitudes are rare when the simulated characteristic is independently generated. As a consequence, the reader should not be impressed with the high magnitude of EHML, given my methodology. What is, in fact, more remarkable is the fact that, in the top IO-deciles, EHML is so low. Having an EHML below 0.50% is a very significant result. In addition, what is "extraordinary" about the results in sub-section 4.1 are both the monotonicity and the wedge between the EHML of high and low IO-deciles. In simulations, no monotonic relationship between IO and EHML has been generated, and the maximum spread (between the EHML of the bottom and top IO-decile) averages 1.4% in the correlated case and 0.5% in the independent case. These findings show that the IO – value premium relationship is robust and meaningful in that it would have required a very intensive search had it been snooped.

6.2. Alternative Risk Models

In sub-section 4.2, we document that the three-factor model fails to explain the relationship between the value premium and IO. In the following sub-section we investigate whether alternative asset pricing models can explain it.

Jagannathan and Wang (1996) point out that the CAPM may fail unconditionally but hold conditionally. Lettau and Ludvingson (2001) and Zhang (2003) propose two different conditional CAPM specifications and show that value stocks are riskier in bad times, which justifies a value premium. For example, Lettau and Ludvingson (2001) argue that value stocks earn higher average returns than growth stocks as they are more highly correlated with consumption growth in bad times. They show that their conditional consumption CAPM – denoted (C)CAPM – captures the value effect far better than unconditional specifications, and about as well as the three-factor model of Fama and French (1993). I then repeat the analysis performed in sub-section 4.2 using the (C)CAPM model and present results in Table 8.[26] The (C)CAPM is partly successful as it breaks the monotonicity and reduces the value premium among low-IO stocks to 1.38%. Nonetheless, the average pricing errors is as large as with the three factor model and the value premium still goes from a high 1.4% for the lowest IO stocks to a non-significant -0.4% for the highest IO stocks. Consequently, I conclude that this model also fails to explain expected returns and, in particular, the relationship between IO and value premium.

Table 8

As a robustness test, I also value-weight the returns in each portfolio and report the resulting change when using the three-factor model. Results in Table 8 show that the decision to equally-weight returns does not affect the IO-EHML relationship. The alpha of low-IO growth stocks, however, appears lower. This finding is explained by what is documented in sub-section 4.2. First, size has no marginal explanatory power beyond IO; hence, once portfolios based on IO are formed, the weighting scheme (equal vs value weights) becomes irrelevant for the value premium. Second, low-IO growth stocks that have a relatively large capitalization had low performance for unknown reasons; possibly by coincidence. Hence, the value-weighted average return of low-IO growth stocks is lower than their equally-weighted average return.

The implied value premium across IO-deciles after adjusting for risk is also reported for the CAPM and the four-factor model of Cahart (1997). Of particular interest, the momentum factor does not help in explaining the above results. This may appear surprising as growth stocks are widely believed to be past winners and value stocks are believed to be past losers. As pointed out in the previous section, this feature does not hold for either low-IO value or low-IO growth stocks.[27] Consequently, the fourth factor (momentum) does not help in explaining the cross-section of IO-BEME portfolio returns.

6.3. Leverage adjustments

Hecht (2002) argues that leverage is the main cause of the value premium. He constructs a value premium for firm (and not stock) returns and finds that it is one third lower than the value premium for stock returns. He concludes that capital structure plays a key role, thereby challenging mispricing theories as the mispricing argument implies a strong value premium for firm returns as well. The fact that HML is much lower for firm returns comes from the fact that value firms are more levered than growth firms and that debt returns is lower than stock returns. The resulting spread between the firm returns of value and growth stocks is then reduced. In order to assess the role played by leverage, one could try to assess debt returns. The market value of each debt contract, along with its corresponding required return is, however, very difficult to estimate. Ferguson and Shockley (2003) recently proposed an alternative and simple methodology. They propose a three-factor model that includes an equity market index and factors based on relative leverage and relative distress. This adjustment should capture the omission of debt in the above analysis. The same procedure as in sub-section 4.2 is then applied by simply replacing HML and SMB by the relative leverage and relative distress factors.[28] The results reported in Table 8 show that the implied value premium remains a strictly decreasing function of IO after such an adjustment. It is a staggering 2.6% in the lowest IO-decile and 0.1% in the highest IO-decile. The fact that leverage considerations do not help explaining the IO-BEME relationship is also consistent with descriptive statistics (Table 1). Low-IO stocks do not display significant difference in terms of leverage while they exhibit a large value premium. Leverage differs for high-IO stocks, but these stocks do not display any value premium.

6.4. Berk's critiques

Advocates of the risk hypothesis may argue that although the risk models that I use do not capture the IO-BEME relationship, other asset pricing models might. Typically, they view BEME as a proxy for the discount rate, which implies, by definition, the existence of a value premium (Berk, 1995). In addition, they further predict a higher value premium among low-IO stocks as these stocks exhibit the most dramatic BEME spread (see Table 1). I test this general claim by running independent cross-sectional OLS regressions of returns on BEME for samples of low-IO, mid-IO, and high-IO stocks. The idea is that the above claim implies that the link between BEME and returns should hold for all sub-samples. In contrast, the mispricing argument implies that the linear relationship between return and BEME should be non-significant for high-IO stocks. Table 9 confirms the mispricing implication. For mid-IO and high-IO stocks (weighing over 95% of the market capitalization), there is no relationship between BEME and returns. In contrast, among low-IO stocks the relationship is very strong (*t*-stat is 2.9).

Table 9

A variant of Berk's critique that is consistent with this finding is that the relationship between BEME and the discount rate is non-linear. It may hold only for stocks with extremely high BEME and since institutional investors do not hold them, the above result is achieved. Yet another possibility is that the dispersion of BEME being lower for high-IO stocks, it is normal to find a weaker relationship between BEME and returns here (Berk, 2000). To address these two points, I eliminate stocks with extreme BEME in the sample of low-IO stocks. This way the dispersion in BEME among (trimmed) low-IO stocks is lower than the dispersion among high-IO stocks. Results show that, even then, the relationship between BEME and returns is very strong among low-IO stocks. Hence, the book-to-market effect is conditional to IO, which is inconsistent with the general risk-based argument.

6.5. Momentum

A natural question that can be raised is whether the above results extend to other stock-market phenomena. In particular, whether one can disentangle the risk and mispricing hypothesis for the momentum pattern, initially documented in Jegadeesh and Titman (1993). When plotting momentum profits against IO-deciles as in graph 1, a concave relationship is obtained. In unreported results, I find that stocks with low-IO exhibit strong reversals for the 6-month/6-month strategy (about -1%), intermediate-IO stocks reaches a 2% momentum return, and high-IO stocks exhibit a low momentum return (about 0.5%). The figures found for low-IO stocks should be interpreted with care, though, as low-IO stocks have returns that are influenced by microstructure biases such as bid-ask bounces or stale prices. This type of argument is typically invoked to remove these stocks when reporting momentum profits. It is unclear to me, however, how microstructure effects can be as long lived as 6 months and that they are that large that they can generate overall reversals of 2% per month (1% of momentum minus 2% of spurious reversal). Nonetheless, an analysis of momentum is beyond the scope of this paper. This result simply indicates that momentum and the value premium are likely to be two distinct phenomena with probably very distinct causes. The tendency of institutional investors to follow trends, style invest, or both (see Barberis and Shleifer, 2003) may be the principal cause of momentum, whereas the exuberance of individual investor for certain stocks is likely to be the main cause of the value premium. In addition, the above result for momentum shows that removing stocks with low stock prices or low-IO stocks greatly influences momentum returns and their link to IO or size.

7. Summary and Conclusion

This paper shows that more than half of the value premium results from stocks with low institutional ownership, which comprise only 7% of the stock market capitalization. In addition, it is shown that a decreasing relationship between institutional ownership and the value premium exists, even after accounting for risk using various asset pricing models. Even the linear relationship between BEME and future returns is exclusive to low-IO stocks. Furthermore, I show that the value premium decreases over time when I account for the time-heterogeneity of the sample. These results are at odds with the "rational" paradigm and suggest that the value premium is created by the tendency of some investors to misprice certain stocks that are, in addition, costly to arbitrage. Nonetheless, the value premium appears to be a relatively small phenomenon, and has, therefore, less empirical and theoretical relevance than often granted to it. In particular, when constructing an asset pricing theory, treating the value premium as a stylized fact of stock price dynamics might be unwarranted. Furthermore, this study stresses the importance of sample selection in studies involving the value premium. Samples focusing on either the largest stocks, stocks followed by analysts, or stocks with a price above $5 are likely to exhibit a very low value premium. Empirical tests of asset pricing models are then expected to be very sensitive to the inclusion of low-IO stocks and the weight assigned to them. In addition, this paper complements an emerging and extensive literature on the role played by institutional investors in financial markets. It suggests that the growing importance of institutional investors may result in the disappearance of certain stock anomalies. Finally, this paper warns that assessing the risk-return trade-off with the three-factor model of Fama and French (1993, 1996), as is widely practiced, may be misleading as HML does not appear to be a compensation for risk.

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Endnotes

[1] Kothari et al. (1995) argue that significant biases arise when analysis is conditioned to assets appearing in both the CRSP and COMPUSTAT databases. This claim is, however, disputed by Chan et al. (1995) and Fama and French (1996). Ball et al. (1995) stress microstructure/liquidity problems when measuring returns of small value stocks. They suggest forming portfolios at June-end instead of December-end. Finally, Lo and MacKinlay (1990) and Conrad et al. (2002) warn against data-snooping; see also the discussion in section 6.

[2] E.g., Fama and French (1993), Lettau and Ludvingson (2001), Gomes et al. (2003), Zhang (2003).

[3] E.g., Lakonishok et al. (1994), Daniel and Titman (1997), and Griffin and Lemmon (2002).

[4] Over the last 20 years, and on an equally-weighted basis, 15% maximum of the value premium came from the short side: even if one could not short growth stocks, one could short the S&P500 and be long on value stocks, which would have generated 85% of the unconstrained value premium. Evidence is even more striking when using the value and growth portfolios of Fama and French. From 1963 to 2001, average returns on the FF-portfolio of value stocks (Ret-v) is 1.4%, average returns on the FF-portfolio of growth stocks (Ret-g) is 1%, and S&P500 average return is 0.7%. From 1980 to 2001, Ret-v is 1.4%, Ret-g is 1.1%, and Ret-S&P is 1%. Hence, an arbitrageur would actually have been better off if she/he could not short growth stocks, and shorted the S&P500 instead, which over these time-periods was relatively easy and cheap to do. Another piece of evidence provided by Nagel (2004) is that stocks held by DFA or Vanguard do not exhibit a value premium. Given that DFA holds mainly mid-cap value stocks, it is not surprising that the value premium in this sub-sample, which is then the difference in the return of the 'most value' mid-cap stocks and 'least value' mid-cap stocks, is low. Similarly, Vanguard holds mainly high-IO stocks, hence no value premium is expected there either, irrespective of the existence of short-sale constraints. The different methodology used by Nagel (2004) also explains why our conclusions diverge. This is discussed in sub-section 4.2 and 4.3.

[5] Nonetheless, debate is on-going about the exact error made by investors. Dechow and Sloan (1997) find no systematic evidence of naive extrapolation of past trends, but argue that prices naively reflect analysts' forecast of future earnings growth. Doukas et al. (2002) point out that there is no systematic mistake in the earnings forecasts for both value and growth stocks. Skinner and Sloan (2002) confirm that growth stocks have as many positive earnings surprises as negative earnings surprises, but respond asymmetrically to negative earnings surprises, which explains most of the growth-value return differential. Finally, Griffin and Lemmon (2002) suggest that investors underestimate the importance of current fundamentals and overestimate the payoffs from future growth opportunities for growth distressed firms.

[6] The economic relevance of short-sales restrictions for asset pricing has been extensively documented in recent academic literature. On the theoretical front, the pioneering model developed by Miller (1977) has been extended by Duffie et al. (2002) to a dynamic environment in which short-selling involves search and bargaining costs. On the empirical front, several papers recently documented the importance of short-sales constraints on stock price dynamics. Of particular interest for this study, Jones and Lamont (2002) and Geczy et al. (2002) find that growth stocks are more expensive to sell short than value stocks. Chen et al.

(2002) similarly document that growth stocks have a low breadth of ownership, signaling that the short-sale constraint is binding.

[7] This argument has to be tempered with the fact that some passive investors, in particular index trackers, are considered as institutional investors. By definition, they cannot be considered as sophisticated.

[8] Implementing the short side for low-IO stocks is also likely to be difficult in the US as, for low and mid-cap stocks, DFA is, by far, the main lender of stocks. This company does not invest in stocks trading at a price below $2, which have a market capitalization of less than 10 million, and mainly propose funds that invest in small value stocks. As a consequence, small growth stocks should be very difficult to borrow (see, http://www.dfafunds.com.)

[9] Other aspects captured by IO such as monitoring (Gillan and Starks, 2000), payout policy (Grinstein and Michaely, 2002), and executive compensation (Hartzell and Starks, 2003) do not hamper my analysis as they do not have, a priori, implications for value versus growth stocks and do not contradict any of the arguments.

[10] The fact that both IO and BEME is persistent (see next section) facilitates the test design as it eliminates timing issues about when the mispricing and the correction occur.

[11] These data can be downloaded on:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I am very grateful to Jim Davis for generously providing me with many details about the data construction. I am also thankful to Pamela Grant for authorizing me to use I/B/E/S data for the present paper.

[12] Several variables exhibit a time trend; hence averages should be interpreted with caution as recent observations are implicitly over-weighed.

[13] Gompers and Metrick (2001) and Bennett, Sias, and Stark (2003) offer a comprehensive discussion of the link between IO and share characteristics. They show how these relationships may change in a regression, in particular the relationship between past performance and IO.

[14] It is interesting to note that across years, the proportion of firms that do not pay dividends has increased overall, but that this phenomenon is concentrated among high-IO firms. A stable 5% of the low-IO firms pay dividends whereas, for high-IO firms, the proportion has decreased from 70% in 1981 to 30% in 2001.

[15] "ILLIQ=1% for stock *x*" means that if an investor trades $1 million worth of stock *x* in a given day, the price impact of the trade is expected to be 1%, that is $10,000.

[16] The quarterly frequency transition matrix is available upon request.

[17] For the lowest IO-decile, in 7% of the cases, IO is reported at zero in June t+1 and in the remaining 18% of the cases there is no valid BEME or Size in June *t*+1.

[18] Especially so, as high-IO value stocks are more levered, pay a higher dividend yield, and have high earnings (or book value) per share compared to their stock prices. Stocks that pay more dividends should have a higher stock return if capital gains are taxed less than dividend gains. Although, in the US, this is generally the case, many institutions have various tax exemptions.

[19] In non-tabulated results, I follow the method used by Fama and French (1993) to form 25 size-BEME portfolios. I simply replace size by IO; that is, I use NYSE breakpoints for IO and value-weight each portfolio, which results in a "dilution" of the low-IO NASDAQ stocks and, therefore, weaken results. The

average pricing errors decrease, but still reach a high 0.17%, which is still twice as high as with the 25 size-BEME portfolios and the GRS statistic strongly rejects the model. Also, I repeated also the construction of the 2 factors by replacing size with IO. The pricing errors are virtually identical to those obtained with HML and SMB. All these results are available upon request.

[20] Lakonishok et al. (1994) use size as a summary variable for arbitrage costs and investor sophistication. Fama and French (1992) and Loughran (1997) show that small stocks exhibit a higher value premium. Loughran (1997) also points out that these small stocks have little weight in terms of market capitalization, and that value stocks outperform growth stocks mainly in January (between 1963 and 1995), commenting that this is "especially disconcerting" for explanations based upon risk or survivorship biases.

[21] In a different sample, Nagel (2003) also finds that IOxBEME is the dominant effect and that IvolxBEME is not marginally significant. This result may be surprising given the evidence reported by Ali et al. (2003). In their table 3, they report that the value premium is higher among high Ivol stocks than among low-IO stocks. The reader should notice, however, that the value premium in the Ivol column is from 1976 to 1997 while the value premium in the IO column is from 1987-1997. Given that the value premium is time varying and tends to decrease over time in certain sub-samples, their result is not conclusive.

[22] Note that Schwert (2002) shows that the value mutual fund DFA US 6-10, designed to capture HML, has not outperformed a CAPM benchmark since its creation in 1994. He then suggests that the value premium has disappeared. However, Houge and Loughran (2003), using a comprehensive sample of value and growth mutual funds from 1965 to 2001, show that value and growth mutual funds have always performed similarly.

[23] I correct for one probable error. HML in February 2000 is -12.05% instead of +12.05%.

[24] The Shapiro-Wilk test for normality indicates that the observations are not normally distributed in the first time-period, hence a *t* test may be misleading. Consequently, I also report a non-parametric test, which is also used in a similar context by Bennett et al. (2003).

[25] An exception is HML in the sample of "All (-fi-pb)". The reason is that the number of financial firms publicly listed has increased over recent years. There are more than 1000 financial common stocks each quarter throughout the 1990s. They tend to be large value firms. In addition, financial common stocks have outperformed the S&P500 by 13% per year on average from 1990 to 2001. Consequently, their inclusion increases the value premium significantly in the 1990s when it is measured as HML, but negligibly when measured as EHML.

[26] I am grateful to M. Lettau for posting the factors: http://pages.stern.nyu.edu/~mlettau/

[27] In addition, Table 1 reports the past 24 months returns while momentum captures an effect for the past 3 to 12 months returns. At such a horizon, the relationship between past performance and BEME is much weaker, which explains that the fourth factor is of no help in this context.

[28] I am grateful to Richard Shockley for his comments and for providing me with the two factors.

Table 1: Descriptive Statistics of Portfolios Sorted on Institutional Ownership

This table reports time-series averages, from 7/1980 to 12/2001, of: institutional ownership (IO), size, monthly return, the total return over the past 24 months (Past Ret), the percentage of firms that have available return data over the last 3 years (3y-listed), the book-to-market ratio (BEME), the dividend yield (DY), the number of analysts following the stock (NAF), the debt to equity ratio (BDME), idiosyncratic volatility (Ivol), and the illiquidity ratio (ILLIQ) of Amihud (2002). Included stocks are traded on the NYSE, AMEX, and NASDAQ and satisfy the following criteria as of July of year *t*+1: i) have data available for the variable of interest, ii) have a positive BEME(*t*), iii) have data about BE(*t*-1), iv) being a non financial common stock, i.e. having an SIC code starting with 6 and a share type code of 10 or 11 v) have a strictly positive IO. Each month, within each IO-decile, quartiles based on BEME are formed. Stocks belonging to the highest (respectively, lowest) BEME-quartile are called value (respectively, growth). Each decile has on average 333 observations. Returns, dividend yields, IO, ILLIQ, Ivol, and 3y-listed are reported in percentage terms and size in millions of US dollars. All characteristics except IO, size, and return are reported separately for value and growth stocks in each decile.

		Low	2	3	4	5	6	7	8	9	High
All	IO	0.68	3.51	7.88	13.21	19.54	26.77	34.85	43.88	53.98	67.82
	Size	27	59	89	152	355	1018	2178	2137	2261	1918
	Return	1.51	1.30	1.43	1.40	1.25	1.27	1.35	1.39	1.38	1.32
Value Stocks	Past Ret	2	8	5	5	8	11	17	20	21	27
	3y-listed	87	91	92	94	95	96	97	97	97	97
	BEME	2.08	2.14	2.10	1.97	1.84	1.75	1.61	1.45	1.37	1.26
	DY	0.22	0.71	0.84	1.73	1.71	2.62	2.83	2.93	2.91	2.92
	NAF	0.15	0.65	1.48	2.45	3.67	5.22	7.21	9.09	11.19	12.77
	BDME	1.61	1.84	1.87	1.54	1.38	1.31	1.32	1.02	0.98	0.97
	Ivol	0.58	0.44	0.36	0.26	0.19	0.14	0.12	0.09	0.07	0.06
	ILLIQ	5.09	3.68	2.29	1.62	1.09	0.83	0.51	0.36	0.27	0.19
Growth Stocks	Past Ret	16	48	51	60	66	70	80	90	94	109
	3y-listed	73	83	82	85	87	88	89	91	92	94
	BEME	0.13	0.17	0.22	0.26	0.27	0.27	0.26	0.24	0.24	0.24
	DY	0.04	0.11	0.14	0.48	0.57	0.64	0.81	1.03	1.02	1.01
	NAF	0.23	0.53	0.83	1.32	2.06	3.36	4.20	5.81	7.01	8.84
	BDME	0.23	0.25	0.26	0.28	0.24	0.24	0.19	0.17	0.14	0.15
	Ivol	0.51	0.35	0.27	0.21	0.17	0.13	0.11	0.09	0.08	0.08
	ILLIQ	2.60	1.60	1.14	0.90	0.63	0.41	0.28	0.16	0.10	0.07

Table 2: Yearly Transition Matrices for IO and BEME

This table reports the transition matrix for IO (panel A) and for BEME categories within each IO-decile (panel B). In panel A, in June of year *t*=1980,..., 2000, stocks with a positive IO are assigned to IO-deciles. I then compute the proportion of stocks in a given decile that falls in decile *d*=low, 2,..., high, in June of year *t*+1. Firms that do not have valid data in June *t*+1 are classified as out. In panel B, I compute the proportion of stocks in decile *d* that move (from June *t* to June *t*+1) from the value category (V) to the growth category (G) and the proportion that stays in the value category and stays in the same IO-decile (V to V s) or move to another decile (V to V o). The same operation is conducted for growth stocks.

Panel A: Transition for IO

t \ t+1	Low	2	3	4	5	6	7	8	9	High	Out
Low	59.9	9.8	3.3	1.4	0.5	0.3	0.2	0.0	0.0	0.0	24.6
2	23.2	43.1	10.8	4.0	1.9	0.9	0.3	0.1	0.1	0.1	15.6
3	4.1	26.7	37.5	11.8	4.3	1.7	0.7	0.4	0.2	0.1	12.5
4	1.4	6.5	27.1	35.5	12.6	4.1	1.8	0.7	0.4	0.3	9.7
5	0.5	2.0	7.5	26.7	34.4	12.2	4.4	1.5	0.7	0.4	9.6
6	0.3	0.8	2.0	7.0	25.7	36.8	13.2	4.4	1.4	0.7	7.7
7	0.1	0.3	0.9	2.0	7.0	24.7	38.8	13.7	3.8	1.5	7.3
8	0.1	0.2	0.4	0.8	2.3	6.4	23.3	41.2	15.6	3.7	6.0
9	0.1	0.2	0.2	0.3	0.8	1.9	5.4	23.2	46.9	15.8	5.2
High	0.2	0.1	0.1	0.2	0.2	0.8	1.6	4.5	20.4	67.4	4.5

Panel B: Transition for Value/Growth

	Low	2	3	4	5	6	7	8	9	High
V to V s	38.4	28.8	23.4	24.4	23.6	27.8	27.9	27.9	36.1	28.3
V to V o	7.2	25.2	35.7	37.2	38.1	39.0	41.2	39.9	37.2	10.3
V to G a	2.3	2.3	1.9	1.7	1.2	1.4	1.2	0.8	0.7	0.5
G to G s	40.9	31.1	26.0	23.7	21.7	24.3	27.4	30.5	34.6	27.4
G to G o	12.1	30.4	36.0	38.9	41.0	39.0	35.6	37.2	35.2	11.4
G to V a	1.0	1.2	0.9	2.1	1.5	1.5	1.2	1.2	1.2	0.5

Table 3: Value Premium and Institutional Ownership

This table reports the relationship between EHML and the level of institutional ownership from 7/1980 to 12/2001. In Panel A, deciles are created monthly according to the last level of institutional ownership reported. Inside each decile, quartiles based on BEME are formed. Stocks belonging to the quartile with the highest (*lowest*) BEME are called value (*growth*). In Panel B, stocks are independently sorted on BEME and IO. EHML is the (time-series) average of the difference between the (cross-sectional, equally weighted) average stock return of the growth and value stocks (RetG and RetV) inside each decile. In Panel A, there are 330 firms on average in each decile. *t*-statistics based on Newey-West autocorrelation-consistent standard errors are reported in italics. In Panel A and B, stocks with an IO reported at zero are excluded while there are included in Panel C. In Panel D, data-snooping benchmarks are computed for the results displayed in Panel A. Two types of simulated-IO are computed: one correlated with the absolute difference between BEME of the stock and the cross-sectional mean (denoted "co"), and one that is generated independently of BEME (denoted "un"). 100 rounds are performed for each type. Each round consists in generating 25 different sets of simulated-IO and running the same computation as above (simply replacing the real-IO by the simulated one). The output is thus 25 series of 10 EHML (one for each decile). Out of these 25, three are kept. One that contains the highest EHML generated (max), one with the lowest (min), and one with the largest difference between the EHML of the top decile and the EHML of the bottom decile. The proportion of rounds in which Max (*Min*) is above (*below*) the figure obtained from Panel A for the corresponding decile is reported as of "Prob(Max>a)|co" for type "co" and "Prob(Max>a)|un" for type "un" *("Prob(Min<a)|co" for type "co" and "Prob(Min<a)|un" for type "un"*). Finally, the number of monotonic relationships obtained (out of 2500) are reported for each type as well as the average (out of 100) of the maximum spread (out of the 25 series) between the EHML of the lowest-simulated-IO-decile and the EHML of the highest-simulated-IO-decile.

Panel A: IO-deciles, dependent sort, zero-IO excluded

	Low	2	3	4	5	6	7	8	9	High	L-H
RetV	2.45	2.13	2.02	1.77	1.54	1.41	1.53	1.51	1.38	1.33	1.12
RetG	0.64	0.51	0.75	0.83	0.67	0.95	1.11	1.24	1.27	1.27	-0.63
EHML	**1.81**	**1.62**	**1.27**	**0.94**	**0.87**	**0.46**	**0.42**	**0.27**	**0.11**	**0.06**	**1.75**
	4.11	*3.99*	*3.43*	*2.72*	*2.79*	*1.48*	*1.56*	*1.06*	*0.43*	*0.22*	*3.38*

Panel B: IO-deciles, independent sort, zero-IO excluded

	Low	2	3	4	5	6	7	8	9	High
RetV	2.47	2.10	2.00	1.78	1.53	1.41	1.55	1.44	1.43	1.33
RetG	0.62	0.52	0.76	0.78	0.57	0.89	1.11	1.24	1.27	1.20
EHML	**1.85**	**1.58**	**1.24**	**1.01**	**0.96**	**0.52**	**0.44**	**0.20**	**0.16**	**0.13**
	4.64	*4.52*	*3.54*	*2.95*	*3.17*	*1.64*	*1.63*	*0.78*	*0.61*	*0.48*

Panel C: IO-quintiles, dependent sort, zero-IO included

	Low	2	3	4	5
RetV	2.43	2.03	1.53	1.54	1.38
RetG	0.78	0.60	0.83	1.09	1.29
EHML	**1.65**	**1.42**	**0.70**	**0.45**	**0.09**
	4.99	*4.42*	*2.49*	*1.84*	*0.37*

Panel D: Data-Snooping Benchmarks

	Simulated-IO-deciles									
	Low	2	3	4	5	6	7	8	9	High
Prob(Max>a)|co	84.7	43.5	99.9	100	100	100	100	100	100	100
Prob(Min<a)|co	100	100	100	95.6	63.1	2.3	1.1	0.2	0	0
Prob(Max>a)|un	0.2	2.2	97.8	99.9	100	100	100	100	100	100
Prob(Min<a)|un	100	100	100	98.2	91.9	89.9	0	0	0	0

	Average of Maximum Spread D-low/D-high	Number of monotonic relationships
Type 1: co	1.4	0
Type 2: un	0.5	0

Table 4: Three-Factor Model and Portfolios Formed on IO and BEME, 1980-2001

This table shows the monthly abnormal performance of 30 portfolios based on the level of institutional ownership (IO) and book-to-market ratio (BEME). The asset pricing model is the three-factor model of Fama and French (FF, 1993) and returns are equally-weighted. Each month, deciles based on (past) IO are formed. Inside each decile, stocks are ranked by their (past) BEME and three groups are formed: the top 25% (called value, denoted V), the bottom 25% (called growth, denoted G), and the rest (denoted I). 30 time-series of portfolio returns (percentage terms) are thus obtained. 30 independent OLS regressions and the following statistics are reported:

i) The estimated coefficient for the intercept and its *t*-statistics as well as the R^2 for each regression.
ii) The implied value premium (Implied Value P.), which is the difference between the alpha of the value portfolio and the growth portfolio.
iii) The *F*-statistic along with its corresponding *P*-value proposed by Gibbons, Ross and Shanken (1989), testing the hypothesis that the regression intercepts are all jointly zero. This statistic is denoted GRS *F*-test.
iv) The average of the absolute value of the 30 estimated alphas, i.e. average pricing errors.

Fama and French (1993) Three-Factor Model: R_t-Rf_t = alpha+b.(Rm_t-Rf_t)+c.SMB_t+d.HML_t+e_t

	alpha					*t*(alpha)				Adjusted R^2		
	G	I	V	**Implied Value P.**		G	I	V		G	I	V
Low	-0.44	0.41	1.32	**1.76**	Low	-0.77	1.15	3.78	Low	0.39	0.53	0.50
2	-0.50	0.21	0.93	**1.42**	2	-1.21	0.76	3.22	2	0.62	0.66	0.58
3	-0.38	0.21	0.66	**1.04**	3	-1.21	1.01	2.51	3	0.72	0.74	0.59
4	-0.25	0.33	0.38	**0.63**	4	-0.95	1.92	1.73	4	0.80	0.80	0.66
5	-0.52	0.10	0.15	**0.67**	5	-2.80	0.82	0.87	5	0.86	0.87	0.75
6	-0.21	0.01	-0.02	**0.20**	6	-1.34	0.07	-0.11	6	0.90	0.90	0.78
7	-0.06	0.09	0.02	**0.08**	7	-0.42	0.84	0.18	7	0.90	0.90	0.82
8	0.10	0.06	0.06	**-0.04**	8	0.75	0.51	0.50	8	0.90	0.89	0.86
9	0.14	-0.03	-0.22	**-0.36**	9	0.95	-0.25	-1.74	9	0.89	0.88	0.85
High	0.16	-0.06	-0.29	**-0.45**	High	0.93	-0.45	-2.13	High	0.87	0.86	0.85

GRS F-test: 4.2 (p= 0.0000)
Average pricing error: 0.28% per month

Table 5: Marginal Effect of Size and Institutional Ownership

This table reports the marginal effect of size and institutional ownership (IO) on EHML. EHML, ReV, ReG, and *t*-statistics are defined as in Table 3. Stocks in panel A are first separated in terciles according to their IO. Then, each of these terciles is divided into three size-terciles. Panel B is formed the same way but stocks are first assigned to size-terciles then to IO-terciles. Finally, the pooled average of IO (in percentage) and size (in million) are reported for each group.

Panel A

	IO-terciles								
	Low			Blend			High		
	Size-terciles			**Size-terciles**			**Size-terciles**		
	Small	Mid	Big	Small	Mid	Big	Small	Mid	Big
ReV	2.93	1.63	1.52	1.62	1.63	1.41	1.42	1.44	1.42
ReG	2.52	-0.01	-0.60	0.92	0.70	0.81	1.10	1.14	1.21
EHML	**0.41**	**1.62**	**2.12**	**0.70**	**0.93**	**0.60**	**0.32**	**0.30**	**0.21**
	0.61	*4.73*	*6.41*	*2.30*	*3.16*	*1.72*	*1.32*	*1.03*	*0.61*
Mean IO	3	5	7	21	24	26	50	55	58
Mean Size	6	19	154	37	92	2124	549	569	5461

Panel B

	Size-terciles								
	Small			Mid			Big		
	IO-terciles			**IO-terciles**			**IO-terciles**		
	Low	Blend	High	Low	Blend	High	Low	Blend	High
ReV	2.64	2.13	1.74	1.55	1.54	1.45	1.54	1.53	1.34
ReG	0.81	1.02	1.22	-0.42	0.61	1.01	0.70	1.31	1.13
EHML	**1.73**	**1.11**	**0.52**	**1.93**	**0.93**	**0.44**	**0.84**	**0.22**	**0.21**
	3.94	*3.32*	*1.61*	*6.02*	*3.33*	*1.61*	*2.33*	*0.73*	*0.94*
Mean IO	1	6	22	9	25	47	26	48	66
Mean Size	12	16	20	82	99	123	2965	3872	2557

Table 6: Marginal Effects of the Main Components of IO – Multivariate Evidence

This table reports the average slope of independent cross-sectional (CS) regressions of individual stock returns on various stock characteristics, from Q3 1980 to Q4 2001. The set of characteristics include the past 6 months returns (MOM), the past book-to-market ratio (BEME), institutional ownership (IO), size, the number of analysts following the stock (NAF), the inverse of the illiquidity ratio ($ILLIQ^{-1}$), the inverse of idiosyncratic volatility ($IVOL^{-1}$), and cross-effects of BEME with IO, size, NAF, $ILLIQ^{-1}$, and $Ivol^{-1}$. Size, BEME, Ivol, and ILLIQ are expressed as ln(X) and NAF as ln(1+X). Finally, the z-score of each dependant variable is computed by subtracting its cross-sectional (CS) mean then dividing by its CS standard deviation. Cross-effects are thus the product of two z-scores. Fama-McBeth *t*-statistics (Newey-West adjustment for autocorrelation) are reported below each coefficient, in italics. Coefficients are multiplied by 100, a constant is included but not reported. In panel B, control variables include all variables in panel A, with the exception of the cross-effects. There are on average 2181 observations per quarter and R-squares average about 8% in each specification.

Panel A: marginal contribution of each cross-effect

	1 (IO)	2 (Size)	3 (NAF)	4 ($ILLIQ^{-1}$)	5 ($Ivol^{-1}$)
MOM	1.93	1.93	1.97	1.98	1.92
	2.25	*2.25*	*2.28*	*2.28*	*2.25*
BEME	1.87	2.07	2.15	2.41	1.67
	2.03	*2.24*	*2.28*	*2.65*	*1.91*
IO	1.66	1.65	1.68	1.78	1.50
	2.19	*2.20*	*2.25*	*2.34*	*2.02*
Size	-5.53	-5.46	-5.54	-5.44	-5.47
	-3.53	*-3.52*	*-3.54*	*-3.50*	*-3.48*
NAF	1.80	1.89	1.94	1.98	1.88
	3.28	*3.36*	*3.37*	*3.44*	*3.37*
$ILLIQ^{-1}$	-0.31	-0.31	-0.31	-0.37	-0.31
	-1.16	*-1.17*	*-1.16*	*-0.58*	*-1.18*
$Ivol^{-1}$	6.85	6.89	6.75	6.67	7.16
	2.71	*2.71*	*2.68*	*2.66*	*2.76*
BEMExIO	-1.87				
	-3.40				
BEMExSize		-1.33			
		-2.46			
BEMExNAF			-1.35		
			-2.83		
BEMEx$ILLIQ^{-1}$				2.42	
				0.31	
BEMEx$Ivol^{-1}$					-1.77
					-3.12

Panel B: IO versus other characteristics

	IO vs Size	IO vs NAF	IO vs ILLIQ	IO vs Ivol
BEMExIO	-1.88	-0.57	-1.88	-1.29
	-3.18	*-3.62*	*-3.42*	*-2.12*
BEMExSize	-0.13			
	-0.24			
BEMExNAF		0.09		
		0.76		
BEMExILLIQ^{-1}			1.90	
			0.25	
BEMExIvol^{-1}				-1.15
				-1.77
Control variables	Yes	Yes	Yes	Yes

Table 7: Dynamic Analysis

This table displays the time-series average of EHML and HML for 5 sub-samples: "All common"- all common stocks in the CRSP database; "All (-fi,-pb)"- like "All common" but excludes financial firms and those for which there is no data on their BE in the previous year; then from "All (-fi,-pb)" I select the 800 largest stocks-"Top 800", stocks listed on the NYSE-"NYSE", and the 50% highest IO stocks-"IO -50%". Samples are rebalanced yearly (July *t* to June *t*+1). The analysis is carried out from July 1964 to December 2001 in Panel A, and from July 1980 to December 2001 in Panel B (due to data restrictions for IO). In Panel A, the average value premium per sub-period for each sub-sample is reported along with the t-statistics. The z-statistics of the rank sum test of Wilcoxon and the standard t-statistic test the null hypothesis that the coefficient estimates in the first and third period are equal. In panel B, I report the average value premium in each sub-sample both for three sub-periods and overall. The proportion of stocks (in terms of market capitalization) that have been removed from "All (-fi,-pb)" is reported in square brackets. Statistical significance is indicated by ** and * for 5% and 10% level test (two tailed) respectively. "HML All (FF)" stands for HML as posted on K. French's website.

Panel A: Test for change in value premium over time

EHML	**All common**	**All (-fi,-pb)**	**NYSE**	**Top 800**
P1: 07/1964-12/1976	0.78	0.79	0.68	0.78
t-stat	*3.05*	*3.07*	*2.50*	*3.09*
P2: 01/1977-06/1989	1.14	1.11	0.60	0.58
	4.77	*4.60*	*2.90*	*2.28*
P3: 07/1989-12/2001	0.84	0.75	0.15	-0.09
	2.52	*2.48*	*0.71*	*-0.22*
P1 vs P3				
Wilcoxon Z-stat	-0.68	-0.88	1.42	2.41**
Difference t-stat	-0.15	0.10	1.53	1.79*
HML	**All common (FF)**	**All (-fi,-pb)**	**NYSE**	**Top 800**
P1: 07/1964-12/1976	0.50	0.60	0.53	0.61
t-stat	*2.35*	*2.82*	*2.57*	*2.54*
P2: 01/1977-06/1989	0.46	0.57	0.45	0.48
	2.16	*2.79*	*2.33*	*2.20*
P3: 07/1989-12/2001	0.23	0.06	0.04	-0.18
	0.77	*0.21*	*0.23*	*-0.50*
P1 vs P3				
Wilcoxon Z-stat	1.28	1.81*	1.71*	2.26**
Difference t-stat	0.72	1.42	1.74*	1.81*

Panel B: Value premium in sub-samples

EHML	**All common**	**All (-fi,-pb)**	**NYSE**	**Top 50% IO**
P0: 07/1980-12/2001	1.10	1.03	0.31 [16%]	0.40 [7%]
P4: 07/1980-08/1987	1.44	1.38	0.47 [12%]	0.82 [7%]
P5: 09/1987-10/1994	1.00	1.00	0.36 [14%]	0.25 [6%]
P6: 11/1994-12/2001	0.86	0.70	0.10 [23%]	0.14 [8%]
HML	**All common (FF)**	**All (-fi,-pb)**	**NYSE**	**Top 50% IO**
P0: 07/1980-12/2001	0.38	0.30	0.19 [16%]	0.12 [7%]
P4: 07/1980-08/1987	0.54	0.56	0.29 [12%]	0.40 [7%]
P5: 09/1987-10/1994	0.28	0.27	0.24 [14%]	0.01 [6%]
P6: 11/1994-12/2001	0.33	0.08	0.04 [23%]	-0.05 [8%]

Table 8: Alternative Asset Pricing Models and Portfolios Formed on IO and BEME, 1980-2001

This table shows how certain asset pricing models capture the time-series of monthly returns of 30 portfolios based on the level of institutional ownership (IO) and book-to-market ratio (BEME). This table is the analog of Table 4. Returns in each portfolio are either equally-weighted (EW) or value-weighted (VW). Asset pricing models used are the three-factor model of Fama and French (1993), the CAPM, the four-factor model of Cahart (1997), the (C)CAPM of Lettau and Ludvingson (2001) and the three-factor model of Ferguson and Shockley (2003). Average pricing errors are computed from the alphas as in Table 4 for all models but the (C)CAPM. For the (C)CAPM, we compute the pricing errors in two steps as done in Table 4 in Lettau and Ludvingson (2001). In addition, this model is estimated quarterly; hence errors are adjusted to obtain a monthly implied value premium.

	Low	2	3	4	5	6	7	8	9	High	Average Pricing Errors
Fama French (1993) – 3 factors - VW											**0.28**
Return Value	0.47	0.49	0.29	0.00	0.24	0.09	-0.09	0.06	-0.25	-0.41	
Return Growth	-1.42	-1.29	-0.53	-0.35	-0.24	0.07	0.01	0.22	0.34	0.25	
Implied Value P.	**1.89**	**1.77**	**0.82**	**0.35**	**0.48**	**0.02**	**-0.10**	**-0.16**	**-0.59**	**-0.66**	
CAPM - EW											**0.46**
Return Value	1.40	1.06	0.99	0.72	0.50	0.36	0.45	0.41	0.24	0.11	
Return Growth	-0.65	-0.89	-0.67	-0.63	-0.76	-0.51	-0.29	-0.17	-0.14	-0.17	
Implied Value P.	**2.05**	**1.95**	**1.66**	**1.35**	**1.25**	**0.86**	**0.74**	**0.58**	**0.39**	**0.29**	
Cahart (1997) – 4 factors - EW											**0.34**
Return Value	1.52	1.21	0.87	0.63	0.30	0.15	0.17	0.22	-0.06	-0.14	
Return Growth	0.16	-0.02	0.09	0.17	-0.20	0.07	0.16	0.25	0.39	0.26	
Implied Value P.	**1.37**	**1.22**	**0.78**	**0.46**	**0.50**	**0.07**	**0.01**	**-0.03**	**-0.44**	**-0.40**	
(C)CAPM – Lettau Ludvingson (2001) - EW											**0.29**
Return Value	0.98	0.67	0.18	0.34	-0.19	-0.55	-0.06	-0.15	-0.12	0.09	
Return Growth	-0.41	-0.21	-0.80	-0.62	-0.42	0.07	0.10	0.15	0.03	0.52	
Implied Value P.	**1.38**	**0.88**	**0.98**	**0.96**	**0.23**	**-0.62**	**-0.16**	**-0.29**	**-0.15**	**-0.42**	
Ferguson Shockley (2003) – 3 factors - EW											**0.43**
Return Value	1.34	0.92	0.76	0.5	0.16	0.16	0.17	0.08	-0.02	-0.08	
Return Growth	-1.26	-1.39	-1.18	-0.93	-1.14	-0.73	-0.51	-0.35	-0.18	-0.21	
Implied Value P.	**2.60**	**2.32**	**1.94**	**1.43**	**1.30**	**0.89**	**0.68**	**0.44**	**0.17**	**0.12**	

Table 9: Regression of Returns on BEME Conditional on Institutional Ownership

This table reports the average slope of independent cross-sectional regressions of individual stock returns on various stock characteristics for 4 different sub-samples of stocks. Each quarter, stocks are separated into IO-terciles and regressions are run within each tercile independently. The trimmed IO-tercile contains the same stocks as the low IO-tercile but omits observations with extreme BEME. In quarter t, a BEME ratio is considered extreme if it is higher than ub_t or lower than lb_t. ub_t (lb_t) is the highest (*lowest*) BEME ratio in the high-IO tercile. All variables described in Table 6 are included as control variables (except cross-effects). The methodology used is also as in Table 6. I report only the results for the coefficient of interest (BEME). The minimum, maximum, mean and standard deviation of BEME in each sub-sample is also reported along with the number of observations.

Dependent variable: individual stock returns				
	IO-terciles			Trimmed IO-tercile
	Low	Blend	High	Low
BEME	3.14	2.06	-0.51	3.65
	2.91	*1.88*	*-0.50*	*3.00*
Control Variables	yes	yes	yes	yes
Nber observations	729	729	729	717
BEME:				
[min;max]	[-9.1;3.2]	[-9.3;2.6]	[-9.5;2.4]	[-6.9;2.3]
[mean;std]	[-0.04;1.1]	[-0.05;1.0]	[-0.08;0.9]	[-0.02;1.0]

Graph 1: Institutional Ownership and Value Premium

Average difference between the monthly return of value and growth stocks (equally-weighted) in each Institutional Ownership (IO)-based deciles.