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DISPOSITION MATTERS: VOLUME, VOLATILITY AND PRICE IMPACT OF BEHAVIOURAL BIAS

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ABSTRACT

Disposition Matters: Volume, Volatility and Price Impact of Behavioural Bias*

We test the market impact of the disposition effect. We rely on the Grinblatt and Han (2002) model and derive testable implications about the expected relationship between the preponderance of disposition investors in the market and stock volatility, return and trading volume. We use a large sample of individual accounts over a six-year period to construct a variable that acts as proxy for the representation in the market of disposition investors. We show that, at a daily frequency, when the fraction of 'irrational' investor trades in a stock increases, stock volatility, return and trading volume decrease. We further show that such a stock-specific disposition acts as proxy to aggregates at the market level, generating a common factor. Statistical exposure to such a disposition-related factor explains cross-sectional differences in daily returns, after controlling for a host of other factors and characteristics.

JEL Classification: D10 and G10
Keywords: asset prices, disposition effect and volatility

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Introduction

An important challenge to behavioral finance is to find a direct link between individual investor behavior and asset price dynamics. Few doubt that large numbers of investors behave irrationally and are prone to behavioral heuristics that lead to sub-optimal investment choices, however the empirical evidence that these investors affect prices, has been elusive. While irrational individual investor traits and tendencies are interesting in their own right, their relevance to asset pricing is limited, unless irrational or at least behaviorally-biased individuals can be shown to be the marginal investors in economically relevant settings. Demonstrating their marginality is a particularly difficult challenge because behavioral data are limited in scope and dimension. Aside from a few limited, natural experiments (cf. Green and Rydqvist, 1999) nobody has yet established an empirical link between the apparent irrationality of investor behavior and changes in asset prices.

This is not to say that evidence on the market impact of individual investor choice is lacking. Warther (1995), Cohen (1999) and Zheng (1999), for example, all find a relationship between aggregate fund flows and equity returns over long periods. Using individual fund flow data, Edelen and Warner (1999) show a high frequency correlation between flow data and the stock returns. Goetzmann and Massa (2000, 2002) establish causality from flows to prices and demonstrate that the aggregate magnitude of the shocks can be large. Goetzmann *et al.* (2000) and Brown *et al.* (2002) find that behavioral factors (orthogonal to standard asset factors) spread asset returns. However, while all of these studies use behavioral factors, the factors are not based on behavioral biases – e.g., loss aversion or disposition effect.

One of the main problems faced by the empirical testing is the fact that most tests of behavioral effects are indirect. They rely on market price, return and volume data, or upon market return anomalies (i.e., overreaction, reversals) as evidence in support of behavioral effects. For nearly all documented return anomalies, however, there are competing rational and behavioral explanations, and it is difficult to design tests with power to reject non-behavioral explanations. For example, Brav and Heaton (2002) compare two competing theories of financial anomalies: "behavioral" theories built on investor irrationality, and "rational structural uncertainty" theories built on incomplete

information about the structure of the economic environment. They show that, alhough the theories relax opposite assumptions of the rational expectations ideal, their mathematical and predictive similarities make them difficult to distinguish. Although the two sets of theories "relax opposite assumptions of the rational expectations ideal, their mathematical and predictive similarities make them difficult to distinguish." Our approach is to link stock returns and volatility directly to individual investor actions. This allows us to demonstrate how investor behavior relates to asset return generating processes. We do so by directly examining the link between behaviorally motivated trades and stock market conditions, in particular, to stock return, volatility and trading volume.

We focus on the most widely documented behavioral heuristic among investors, the *disposition effect*. The disposition effect was introduced to finance literature by Shefrin and Statman (1985) as a characterization of the tendency of individuals to ride losses and realize gains. As such, it was based directly on Kahneman and Tversky's loss aversion framework. While extensive empirical and experimental evidence of this effect exists (e.g., Barber and Odean, 2000, 2001, 2002, Weber and Camerer, 1998), the link between such a bias and stock market conditions has been scarce. Using *indirect* evidence based on stock prices, Grinblatt and Han (2002) show that U.S. stocks with large, unrealized capital gains have higher expected returns – exactly what their model of the disposition effect would predict. Their results strongly suggest that a disposition factor constructed directly from individual investor decisions should directly impact the stock market.

In this paper we concentrate on *direct* evidence. We exploit a database of individual investor decisions to construct a proxy that captures the representation of the disposition effect for each stock and to test how it affects stock returns, volatility and trading volume. This allows us to directly bring to the data the restrictions of the model of Grinblatt and Han (2002). We document a strong and statistically significant negative correlation between the disposition effect and stock return, volatility and trading volume, as theory predicts. This supports the intuition that the disposition effect dampens the stock reaction to shocks to the fundamentals, reducing return, volatility and trading volume. Our results are robust to different specifications, alternative econometric

methodologies and different ways of constructing the disposition proxy. Moreover, we also use out-of-sample testing that controls for potential spurious correlation that could arise when conditioning on current prices.

Then, we move to the aggregate level and study whether the disposition effect aggregates at the overall market level. We construct a market-wide measure of the disposition effect by aggregating the disposition proxies for the different stocks, and study how stock-specific returns, volatility and trading volume are related to it. We show a strong negative correlation between these stock specific variables and the aggregate market disposition effect. We interpret this as evidence of the existence of a common disposition effect that affects the overall market.

Finally, we see whether this aggregate disposition factor spread returns. Using a standard Fama and MacBeth methodology, we provide evidence that stock returns load on the common disposition factor. The disposition factor acts like a discount factor and the more the stocks load on it, the lower is their required rate of return. While all this evidence is consistent with the hypothesis that trade between disposition investors and their counter-parties influences relative prices, it is interesting to note that this lower return is not due to an increase in stock (or market) liquidity. Quite the contrary, the disposition effect seems to reduce it.

Our results are important as they provide a direct evidence of the role of a behavioral bias in financial markets. The existence of disposition-prone investors muffles the stock reaction to shocks to the fundamentals. At the market level, this implies a generalized attenuation of the reactivity of the market. This would suggest that the disposition effect plays a beneficial role during periods of crises. The higher the percentage of disposition-prone investors, the more stable the market should be. This has relevant implications for normative purposes too. In as much as the disposition effect is a bias, it may depend on the investors' degree of financial literacy and may therefore change as markets evolve, and decrease over time. However, this "learning" process of the investors is not necessarily entirely beneficial, as it may reduce an important source of stability.

The remainder of the paper is structured as follows. In Section 1, we relate to the existing literature. In Section 2, we develop testable restrictions. In Section 3, we

describe the data we use. In Section 4, we explain the construction of our behavioral factors. In Section 5 and 6, we describe the empirical tests and the results. A brief conclusion follows.

1. Background

Behavioral theory argues that prior gains induce a behavior different from that induced by prior losses. Loss aversion postulates that prior losses increase risk-taking, while prior gains reduce it. In particular, investors have the "tendency to seek risk when faced with possible losses, and to avoid risk when a certain gain is possible." (Kahneman and Tversky, 1979). Loss aversion relies on psychological studies, which show that a decline in utility arising out of the realization of losses relative to gains, induces investors not to sell losing stocks relative to winning ones.

This intuition, formally developed by Kahneman and Tversky (1979), has been applied empirically to the financial markets by Shefrin and Statman (1985) and Benartzi and Thaler (1995). In a financial setting, "the reference point effect explains the disposition to sell winning stocks too early and ride losing stocks too long" (Shefrin and Statman, 1985). Shefrin and Statman (1985) predicted that because people dislike incurring losses much more than they enjoy making gains, and people are willing to gamble in the domain of losses, investors will hold onto stocks that have lost value (relative to the reference point of their purchase) and will be eager to sell stocks that have risen in value. They called this the disposition effect. Statman and Thorley (1999) point out that this bias, being based on a mental accounting framework, is stock-specific rather than related to the market as a whole.

Empirical support to this theory has been provided by Barber and Odean (2000, 2001, 2002) and Odean (1998, 1999). They showed that investors do indeed tend to hold losers and sell winners. Widespread evidence of loss-aversion and the disposition effect has since been found and explored by other authors. Weber and Camerer (1998) and Weber and Zuchel (2001) have experimentally documented the effect for investors. Oehler *et al*. (2002) show that it is pervasive across markets around the world. Dhar and Zhu (2002) find that the tendency towards the disposition effect differs among individual

investors, depending upon personal characteristics. Grinblatt and Keloharju (2000) find strong evidence of loss aversion in Finnish data, and Genesove and Mayer (2001) shed further light on investor irrationality by analyzing loss aversion and seller behavior in the housing market. More recently, Jackson (2002), and Brown, *et al.*, (2002) using Australian data, provided evidence on the "half-life" of the disposition effect among investors. Barber, Odean and Zhu (2003), show that the net trading of individuals is "highly correlated and more coordinated than one would expect by mere chance". They argue that behavioral biases – especially the disposition effect – are "the most plausible drivers of the coordinated trading". This coordination would suggest the potential for observing a pricing impact for the disposition effect.

Considerable theoretical analysis also suggests that behavioral biases could affect asset prices. For example, Shumway (1997) develops an equilibrium asset-pricing model based on loss-averse investors and shows that loss aversion induces investors to demand a higher risk premium for risk associated with negative market returns. Grinblatt and Han (2002) develop a theoretical model to explain the equilibrium price implications of the disposition effect. This allows them to relate momentum to the amount of unrealized capital gains/losses, and to derive cross-sectional implications they use to test their model. They find that a capital gains variable has pricing implications, a result that would be implied by the salience of disposition investors.

However, scarce direct evidence of the impact of behavioral biases on prices has been provided. Coval and Shumway (2001) report evidence of behavioral biases among proprietary traders at the Chicago Board of Trade and investigate the impact of such biases on prices. They show that losing traders tend to buy contracts at higher prices and sell contracts at lower prices and they document a short-term price impact. Kaustia's (2001) study of IPOs finds evidence that the disposition effect impacts the prices of recently issued stocks. Our goal is to bridge this gap.

2. Analytical Framework

We rely on the model developed by Grinblatt and Han (2002). They derive closed-forms for the stock price and the trading volume as a function of fundamentals and disposition variables. We adopt their specification and refer the reader to their paper for further detail.[1]

2.1 The disposition effect and stocks

We start considering the impact of the disposition effect on stock return and volatility. The price of an asset (P_t) can be defined as:

$$P_t = wF_t + (1-w)R_t, \tag{1}$$

where F_t is the fundamental value of the asset and R_t is the reference price of disposition investors.[2] The variable w is the weight that accounts for the representation of the disposition investors in the market. In particular, $w = \frac{1}{1+\mu}$, where μ is the proportion of disposition investors. w proxies for the impact of disposition investors in the market. It is decreasing in the fraction of the disposition investors in the market (μ). The reference price is the weighted average of the past prices at which the disposition investors executed previous trades, determined according to the updating rule: $R_t = v_{t-1}P_{t-1} + (1-v_{t-1})R_{t-1}$. The variable v_t defines the update of the reference price on the basis of date t information and is bounded between 0 and 1. We can therefore rewrite equation 1) as:

$$P_t = wF_t + (1-w)[v_{t-1}P_{t-1} + (1-v_{t-1})R_{t-1}] \tag{2}$$

[1] We assume for simplicity that the relative intensity of the demand perturbation induced by the disposition effect and the slope of the rational component of the demand function have unitary value.

[2] A "disposition-prone" investor is one with a greater propensity to sell stock to recognize gains as opposed to selling stocks to recognize losses. Kahneman and Tversky (1979) show that a positively sloped utility function in asset returns with a second derivative that changes sign from negative to positive at an investor-specific reference point will induce disposition-like behavior in trades. Barber and Odean (2000) point out that this behavior is contrary to a capital-gains tax minimizing strategy and thus is costly if not irrational.

The intuition behind equation 2) is that the price of a stock is a function of both the fundamentals (F_t) and the accumulated impact of prior capital gains/losses (R_t), weighted by the factor representing the impact of disposition investors (w). We can therefore define stock return (Ret_t) and volatility (σ_t) as:

$$Ret_t = \frac{P_{t+1} - P_t}{P_t} = \frac{w}{wF_t + (1-w)R_t}\varepsilon_{t+1} + \eta_t \text{ , and } \sigma_t = \frac{w}{wF_t + (1-w)R_t}\sigma_\varepsilon , \qquad (3)$$

where σ_ε is the volatility of the shocks to the fundamentals.

The return on a stock is a function of a backward looking component (η_t) and of the shocks to the fundamentals (ε_{t+1}), amplified or shrunk by the disposition effect. This clearly illustrates the role played by the disposition effect. The stock price "under-reacts to public information about the fundamental value, holding the reference price constant" (Grinblatt and Hand, 2002). That is, the disposition effect drives a wedge between the fundamental value of an asset and its market price. The higher is the fraction of the disposition investors, the lower the sensitivity of the price to current shocks to the fundamentals. Notice that here we do not assume that investors change their tendency towards the disposition effect on a daily basis or that investors who are constantly prone to the disposition effect change their "participation" in the market on a daily basis. The model simply shows that the presence of disposition-prone investors amplifies/reduces price fluctuations.

Grinblatt and Han test these restrictions by focusing on momentum and assessing the role of past gains and losses on stock returns, using a gains variable constructed from past returns and turnover. A stock that has had positive momentum for a while (i.e., a winner) must have a positive spread between fundamental value and market price that is related to the existence and the position and size of disposition investors. Therefore, the aggregate amount of unrealized capital gains provides a way to test the impact of the disposition effect.

Note however that if the data were available, a more powerful test could be based on the inspection of the representation of disposition investors in the market (μ). In particular, it easy to verify that equation 3) implies that: $\frac{\partial Ret_t}{\partial \mu} < 0$, and $\frac{\partial \sigma_t}{\partial \mu} < 0$. The intuition is that the stocks that are mostly traded by disposition investors (i.e., μ is high),

will have a lower sensitivity to fundamental shocks and therefore will have a lower return and volatility. Therefore, conditional on a fundamental shock, all stocks will be affected with intensity depending on the representation of the disposition investors in the market.

These considerations suggest that a direct test of the impact of the disposition effect relies on the estimation of the relationship between the fraction of disposition investors trading a specific stock, and the stock return and volatility. The null of zero relationship between the percentage of disposition investors in the market, and returns and volatility, is tested against the alternative of a negative relationship between them.

It is important to notice that the model implies a negative contemporaneous correlation between the representation of disposition investors in the market and returns. In other words, when investors, who have been identified as more willing to sell gains than losses, are selling, the market tends to go up. This would also be consistent with a reverse causality in which, when prices rise, investors who prefer to sell for a gain sell more. This is why the test on volatility is important. Indeed, given that investors are defined as disposition prone on the basis of their willingness to hold on to the losing stocks, there should not be any direct relationship between their definition and volatility. Theory would not suggest that disposition-prone investors are more willing to sell (buy) during period of high (low) volatility. This suggests that the restriction on volatility provides an important identifying restriction for our story.

Finally, we can also consider the relationship between the disposition effect and trading volume. Grinblatt and Han show that trading volume is:

$$E[V_{t+1}] = \mu(1-\mu)wE[|\varepsilon_{t+1} - \nu_t(P_t - R_t)|] = 2\mu\frac{1-\mu}{1+\mu}\sqrt{\frac{2}{\pi}}\sigma_\varepsilon^2, \qquad (4)$$

It can be easily seen that the impact of a change in the proportion of the disposition investors (μ) depends on the size of μ itself. For low values (approximately $\mu<0.4$) an increase of μ increases trading volume, while for higher levels ($\mu>0.4$) an increase of μ reduces trading volume. Therefore, in this case the empirical results depend on the sample properties and we will let the data talk. It is worth noting that in Grinblatt and Han's model, trading volume and turnover coincide, so the restrictions in equation 4) hold for both turnover and trading volume.

2.2 The disposition effect and the overall stock market

The previous restrictions suggest that the disposition effect may affect stock volatility, return and trading volume by muffling the stocks' sensitivity to shocks to the fundamentals – the only source of uncertainty in the Grinblatt and Han's model.

However, we can also have a shock to the representation of disposition investors in the market itself. That is, we can assume that some exogenous event (e.g., liquidity shock) changes their representation in the market. A change in the representation of the disposition investors in the overall market has a direct impact on returns and volatility. Let us see why this is the case. We know that disposition investors tend to hold losers and sell winners. This implies that, if the stocks are doing well and prices are above the reference point,[3] an increase in the fraction of disposition investors (i.e., the holders of losing stocks and sellers of winning stocks) reduces net demand, thus lowering prices (P_{t+1}), returns, and volatility. If this effect aggregates at the market level, changes in the representation of disposition investors may behave as a market factor. Stocks with a positive loading on it, i.e., stocks whose disposition-motivated trades increase with the increase of disposition-motivated trades in the market – should have a lower return and trade at a discount. Conversely, stocks with a negative loading on it – i.e., stocks whose disposition-motivated trades decrease with an increase of disposition-motivated trades at the market level – should have a higher return and trade at a premium. In other words, stocks for which the fraction of disposition investors is lower, should command a higher return, while stocks for which the fraction of disposition investors is higher, should have a lower return.

This reasoning follows Pastor and Stambaugh (2002) who point out that the order flow represents a source of uncertainty of its own. In our model, order flow is a function of the prevalence of disposition investors in the market. Thus, the fraction of trades by disposition investors in the market represents a non-diversifiable source of uncertainty. Market-wide shocks to the disposition factor – proxied by the unexpected shocks to the fraction of disposition investors – represent "a state variable important for asset pricing. Expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate" disposition effect. The source of these shocks – the results of

3 It can be shown that if $F_{t+1} > R_{t+1}$, we also have that $P_{t+1} > R_{t+1}$.

the aggregation of stock-specific transaction-related shocks – can be due to fluctuations in the level of the disposition investors. An increase of μ reduces stock return and volatility. Given that it cannot be forecast by the investors, this change generates uncertainty that, if aggregated at the market level, should be priced.

In order to test the restrictions mentioned above, we proceed as follows. First we construct a variable that proxies for the representation in the market of disposition-motivated investors. We will call this proxy the "disposition proxy". We use this proxy to relate stock return, volatility and trading volume to the disposition effect, testing the restrictions. Finally, we provide some evidence on whether the disposition effect aggregates at the market level and produces a common factor on which stock returns load.

3. Data

We use data provided by a nationwide discount brokerage house. The dataset is that previously used by Barber and Odean (2000, 2001, 2002), Odean (1998, 1999) and Barber, Odean and Zhu (2003). We refer to it hereafter as the "Individual Investor Database" or IID. The IID contains information on over 100,000 accounts for around 80,000 households. For each account, we have the position files that contain the end-of-month investor portfolios and the daily transactions of all the assets for the period 1/1/1991-28/11/1996. For each transaction in the account, we know the security traded (identified in the case of a stock by the CRSP CUSIP), the direction of the trade, the number of shares traded, and the commission paid. For each account, we also have some demographic information about the investor. Each investor may hold several accounts. We follow Barber and Odean and concentrate only on their equity holdings. We conduct our analysis at the investor level – i.e., concentrating the different account of the same investor – and consider each single buy and sell order for each account. Indeed, there is no substantial reason to believe that the same investor behaves significantly differently in different accounts. For a more detailed description of the data we refer to Barber and Odean (2000, 2001, 2002) and Odean (1998, 1999).

We report descriptive statistics in Table 1. In particular, in Panel A, descriptive statistics for groups of accounts are broken down on the basis of the average number of transactions per year. For each group, we report the number of accounts, the number of transactions and the percentage (out of the total transactions) of purchases and sales. We also report the average running balance and the turnover ratio. The running balance is constructed as the average holdings standardised by the amount of time they are held.[4] Turnover is calculated as the absolute sum of purchases and sales (expressed in terms of number of shares) divided by the average running balance. In Panel B, we report some disposition characteristics. That is, for each group, we separately consider the buy-at-gain, buy-at-loss, sell-at-gain and sell-at-loss transactions, as described in the next section. For each of these categories of transactions, we report the number of transactions and their percentage in terms of number of overall transactions.

In order to draw inferences about the potential effects of the behavior of one class of investors on asset prices, it is necessary to have a representative sample. This is a general issue addressed by many previous authors with respect to the IID. For example, Kumar (2002) compares the sample to that reported by the Census Bureau (Survey of Income and Program participation, (SIPP), 1995) and the Federal Reserve (Survey of Consumer Finance (SCF), 1992, 1995). The median portfolio size of an individual investor portfolio in the IID is $13,869. This is close to the $16,900 account size for the SCF 1992 and to $15,300 account size for SCF 1995. Moreover, as reported by Barber and Odean (2000, 2001, 2002), the IID does not appear to be overly geographically focused, or limited in terms of the distribution of the income or trading characteristics. It is worth stressing that, given that our analysis is based on daily frequency, the sample is particularly suited to represent the daily trading behavior of an *average* US retail investor on the market.[5]

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[4] We construct H by weighting the number of shares (N) an investor holds between the purchase date (b) of the shares and the sales date (s) of the shares, that is: $H_i = \sum_{t=b}^{s} N_{i,t}(s-b)$. We then divide this by the number of days the account is open in the period to calculate running balance. That is, the difference between first and last holding dates for investor i: $RB_i = \frac{H_i}{\max(t_i) - \min(t_i)}$.

[5] Some of the transactions are carried out over the internet (for details, see Barber and Odean, 2002).

4 Construction of the variables

The fact that the dataset was used to assess the existence of the disposition bias (Odean, 1998), allows us to skip the preliminary step of showing the existence of such a bias in the sample. Moreover, we can directly appeal to recent evidence that shows that such a bias induces investors to co-ordinate their trades (Barber, Odean and Zhu, 2003). This suggests that the disposition bias, by inducing co-movements in trade, could potentially have a market impact. Our study simply takes the next logical step by constructing variables that proxy for such disposition-based factors and linking them to stock price, volatility and trading volume.

One possible objection to this approach is the issue of representativeness. Is our sample of 100,000 accounts big enough to allow us to make inferences about the entire investor population? Were this group randomly drawn from the population, the answer would be yes. If it is a non-random sample, biased perhaps towards jointly disposition-prone and infra-marginal investors, then the generality of our results might be questioned. Although the brokerage sample may be tilted towards more active individual investors and does not represent institutional traders, it is unlikely that it has a strong bias with respect to behavioral characteristics, or for that matter towards price-setters in the capital markets. Thus, if anything, we are working with a sample that allows a relatively weak test of the price impact of the disposition effect. Fortunately, we know from the literature (Barber and Odean, 2000, 2001, 2002) that our sample is representative at least in terms of containing disposition investors. It is indeed *the* sample where disposition effects have been documented.

The second issue deals with the probability that the investors in our sample are carrying stocks at a loss/gain with respect to the current price, in the same way as the population of investors in the market does. This depends on the current price as well as on the prior transaction history of each investor, i.e., the price at which they bought/sold and therefore the moment at which they executed the prior transactions. Therefore, for our sample to be representative, we require that our investors, on average, trade in the same way as the population of US investors does. If this is the case and our investors are truly representative of the US market, the factors we identify are representative of the

behavior of the average investor.[6] Work by others with this sample suggests that temporal changes in the aggregate volume of trade in the sample are generally representative of the volume fluctuations for the stocks as a whole. Thus, we have no reason to expect that our sample is biased with respect to the accumulation of unrealized gains and losses of the individual investing population in the U.S. as a whole. However, a caveat always applies.

4.1 Constructing the disposition proxy

To construct our disposition proxy, we first identify the disposition investors and then use their trades to determine the representation of the disposition investors for each stock and day. We proceed as follows. We identify disposition investors on a transaction basis, relying on the Barber and Odean (2000, 2001, 2002) results. More specifically, for each transaction, we distinguish trades "at-loss" and trades "at-gain". Then, for each stock, we construct a daily time series of the "sales-at-loss", "sales-at-gains", "buys-at-loss" and "buys-at-gains."

In order to identify "sales-at-loss", we have to make some assumptions about the previous price at which the stock was purchased. We assume a "LIFO" criterion for each single investor.[7] That is, the last shares bought are assumed to be the first ones sold.[8] For example, consider the following sequence of transactions for a given investor at the beginning of the sample, January 1991. First, a "buy" happens at a particular price. Next, if a "sell" occurs in the next period, then we calculate the difference between the sell price and the price at which the previous purchase occurred. If the difference is negative, i.e., if the sale occurred at a price lower than the price at which it was previously bought, we record this as a "sale-at-loss." If, on the contrary, the difference is positive, we consider it a "sale-at-gain."

For each sale, the quantity is compared to the quantities previously bought. If the quantity is lower or equal to the number of shares bought in the previous purchase transaction, the profit or loss is given by the difference between the prices of the two

[6] In our sample we are omitting the institutional investors. However, these mostly take the other side of the market with respect to the individual investors (Cohen, Gompers, Vuolteenaho, 2001).
[7] That is for each single investor we aggregate the different accounts.
[8] Every sell until the first buy operation within the period 1991-1996 is ignored.

transactions. If, however, the quantity sold is greater that the number of shares purchased in the transaction immediately before, we use the LIFO criterion and refer back to earlier purchases, until we have fully matched the current shares sold with previous purchase transactions. We then calculate the profit/loss of the sale by weighting the quantity previously purchased by the price at which the transaction took place.

The LIFO criterion is, of course, a necessary accounting convenience adopted for our analysis. Its validity or relationship to the disposition effect has not been tested experimentally, despite its intuitive appeal. Thus, it is conceivable that it could make our measure of the disposition effect less than perfect. Nevertheless, it is not clear why this approach would bias our results one way or the other. Let us look at a sample case (e.g., IBM):

Transaction date	Quantity	Price	Buy/Sell	Gain/Loss
910101	100	100	Buy	-
910105	100	110	Buy	(110-100)*100 = 1,000
910110	200	70	Buy	(70-110)*200 = -8,000
940101	310	150	Sell	(150-70)*200+(150-110)*100+(150-100)*10 = 20,500
950103	50	110	Sell	(110-100)*50 = 500

For the above data we compute the gain/loss measures in the following manner. We start with the first buy operation on 01-01-1991. Calculation of the gain/loss for this transaction is indeterminate. Next, 100 shares are purchased on 01-05-91. So the "buy-on-gain" is equal to: 100 x (110-100) = 1,000. The next purchase is a "buy-on-loss". That is, the loss is equal to: 200 x (70-110) = -8,000. The next transaction is a sell. The investor is selling 310 at a price 150. Out of these 310 units, the first 200 units are compared to the previous purchase price of 70, the next 100 would be compared to the purchase price of 110, and the next 10 would be compared to the purchase price of 100. So the total would be 200 x (150 – 70) + 100 x (150 – 110) + 10 x (150 – 100) = 20,500. This represents a "sell-on-gain," realizing profit.

It is worth noting that we use the same convention for both buys and sells. That is, for each sale transaction, we identify whether it was a profit or loss, from the investor's standpoint. Analogously, in the case of purchases, using the previous transaction of the

investor as anchor or reference point, we identify whether it took place at a loss - where the investor lost with respect to his previous transactions - or whether he gained.

We proxy for the representation in the market of the disposition effect by using the ratio of the disposition-motivated trades over the overall trades in the market. In order to identify the disposition-motivated trades, we use as criterion the fact that disposition investors tend to hold on to the losing stocks and sell the winning ones (i.e., "sell-at-gain"). This implies that a proxy can be directly related to the fractions of investors who sell-at-loss and those who sell-at-gain. In particular, we define a variable W that is constructed as the difference between the total dollar value of "sells-at-loss" and "sells-at-gain", standardized by the sum of "sells-at-loss" and "sells-at-gain", that is:

$$W_t = \frac{\left(S_{lt} - S_{gt}\right)}{\left(S_{lt} + S_{gt}\right)}, \qquad (5)$$

where, S_{lt} and S_{gt} are, respectively, "sell-at-loss" and "sell-at-gain" transactions for day t. This variable increases as the value of "sales-at-gain" gets smaller than the value of "sales-at-loss", i.e., it increases as the sales by the disposition investors (S_{gt}) shrinks with respect to the sales by the non-disposition ones (S_{lt}). In other words, this variable is greater for stocks for which the representation of disposition investors among the sellers is smaller. That is, this variable increases as μ increases.[9] Given that, according to equation 3), an increase of μ is negatively related to returns, we expect that, stocks for which W is higher, experience lower volatility and return.

W is directly related to the spirit of the disposition effect – selling winners and holding onto the losers – and therefore will be our main disposition proxy. However, as additional robustness checks, we also construct variables that use the information contained in the buys. In particular, if we assume that disposition investors sell the winning stock *and buy losing stocks*[10] (i.e., "buy-at-loss"); we can construct other two

[9] Indeed, the fewer disposition investors are among the sellers, the higher should be the representation of the disposition investors among the net demand (or resulting net holding as defined in equations 1 and 2 of Grinblatt and Han paper) of the stock.

[10] We can think of the disposition investors as holding on to losing stocks. So, if they dynamically rebalance their portfolio over time, they appear to be buying losing (with respect to their reference point) stocks more often that the non-disposition investors. This would show up as a positive difference between their buys-at-loss and the buy-at-loss of the non-disposition investors. So, on average, we may expect that the amount of buys-at-loss proxies for purchases by disposition investors. The buy-at-gains should, instead,

proxies. The first proxy (W_p) is constructed as the dollar-value of total "buys-at-loss" minus "buys-at-gain" on a given day, standardized by the sum of "buys-at-loss" and "buys-at-gain". The second alternative proxy (W_{ps}) combines the information from "buys-at-loss" and "sells-at-loss". It is constructed as the difference between "buy-at-loss" plus "sell-at-loss" and "sell-at-gain" minus "buy-at-gain" standardized by the sum of "buy-at-loss", "buy-at-gain", "sell-at-loss" and "sell-at-gain". In particular, the other two proxies are:

$$W_{p,t} = \frac{(B_{lt} - B_{gt})}{(B_{lt} + B_{gt})}, \text{ and } W_{ps,t} = \frac{(S_{lt} - S_{gt}) + (B_{lt} - B_{gt})}{(S_{lt} + S_{gt}) + (B_{lt} + B_{gt})},$$

where B_{lt}, B_{gt}, S_{lt} and S_{gt} are, respectively, "buy-at-loss", "buy-at-gain", "sell-at-loss" and "sell-at-gain" transactions. Note that the reference point is always the price at which the investor's previous transaction was executed under the LIFO criterion. This may date back as much as five years in our sample.

This approach, while having the advantage of being transaction-based and allows for time-variation in the degree of the disposition effect, is not immune from criticism. Indeed, it may classify as disposition-motivated those transactions that have been carried out to just close a successful speculative position. Moreover, it may be subject to the issue of spurious correlation with momentum strategies. However, it is important to notice that the fact that the position is at "at-loss" or "at gain" is determined on the basis of each investor's reference price. This can date back as much as 6 years in our dataset. This implies that the same current price may originate a loss for an investor and a gain for another, depending on when the previous "originating" transaction (purchase in case of current sale or sale in case of current purchase) took place. Therefore, the potential spurious correlation with current prices and with momentum strategies should be very low. In any case, to directly address this issue, we also consider a second approach.

4.2 An alternative way of constructing the disposition proxy

A second way of identifying the disposition investors is on an out-of-sample basis. That is, we first define as disposition-prone the investors who, in a month, have

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proxy for the purchases by non-disposition investors. Indeed, if disposition investors sell the winning (with respect to their reference point) stocks, they should not simultaneously buy them back.

"sold winners and held on to losers" and then we trace their behavior in the following month. This procedure, reminiscent of the cross-validation methodology of Conway and Reinganum (1980), allows us to define the investors in-sample and to construct the behavioral factors out-of- sample, avoiding the selection bias. To implement it, we follow the same methodology developed by Odean (1998). We provide here a general description and we refer to his paper for a more detailed exposition.

For each investor, we focus on his *realized* gains/losses and his *paper* gains/losses. Each day, we identify for each investor his *realized* gains/losses. These are constructed by comparing the selling price for each stock sold to its purchase price. We define as purchase price the one based on the methodology before described.

For all the other stocks that are in the portfolio and are not sold, we also construct the daily *paper* gain/losses by comparing the purchase price of each stock (i.e., the price at which it is held in the portfolio) to the stock's high and low price for that day. If both the daily high and low are above the purchase price, this is counted as a *paper* gain; if they are both below it is counted as a *paper* loss; if its purchase price lies between the high and the low, neither a gain nor loss is counted. For each day, all the *paper* gains/losses for a particular stock are accumulated, as well as the *realized* gains/losses.

Then, for each investor we aggregate at the end of the month all the daily *paper* gains/losses as well as the daily *realized* gains/losses, and construct for each investor the following ratios:

$$PGR = Proportion\ of\ Gains\ Realized = \ PGR = \frac{RealizedGains}{RealizedGains + PaperGains}$$

$$PLR = Proportion\ of\ Losses\ Realized = \ PLR = \frac{RealizedLosses}{RealizedLosses + PaperLosses}.$$

We use these ratios to identify the disposition investors. In particular, following Odean (1998), we define as disposition-prone the investors for which PGR > PLR, where these ratios are based on the value of the prior month losses/gains.

This classification is done for each month. Then, we trace the behavior of the different classes of investors in the following month. That is, *the following month*, each day, we separately identify the trades of the different classes of investors and we use

them to construct our disposition proxy. This variable – constructed as the difference between the trades of disposition investors and trades of the rest of the market, standardized by total trades – represents the representation of the disposition investors in the market (μ) and should be negatively related to both stock volatility and return.

4.3 Construction of other variables

We use daily data on the 100 largest (by market capitalization) stocks in the U.S. market at the beginning of the period. We select these stocks as more trades are carried out for these stocks and this increases the power of our test. Indeed, after the first 100 stocks, the number of trades drops drastically. Therefore, even if we expect that retail investors have more impact on small stocks than big stocks, still the number of trades would be too small to properly construct our proxies of disposition trades and to run a meaningful analysis. Moreover, the very fact that big stocks are heavily traded by institutional investors, biases the test against us, making it harder to find a relation.[11]

We use two measures of volume. The first is trading volume, measured by the logarithm of the number of shares traded and the second is the logarithm of turnover, defined as volume divided by the outstanding number of shares. Previous authors, i.e. Anshuman, Brennan (2001) and Chordia and Subrahmanyam, (2001), find that turnover is a "characteristic" that affects the return of each stock.

Given the daily frequency of the data, we use a range-based measure of volatility. Alizadeh, Brandt and Diebold, (2001 and 2002) recently showed that that "theoretically, numerically and empirically, the range-based measure of volatility is not only a highly efficient volatility proxy, but also that it is approximately Gaussian and robust to microstructure noise." Thus, for each stock we construct volatility as the log percentage range:

$$\sigma_t = log\left[max_{\{s \in Day_t\}} P_{s,t} - min_{\{s \in Day_t\}} P_{s,t}\right]. \qquad (6)$$

[11] Institutions take the other side of the trade, exploiting retail investors' behavior (Cohen, Gompers, Vuolteenaho, 2002). Therefore, retail investors' trade should directly impact institutions' trades and therefore prices.

where, daily volatility is defined as the log range between the highest price of the day minus the lowest price of the day (i.e., for each time *s* in the *tth* day). We omit the subscript *i* to denote the *ith* stock for simplicity.

The analysis is based on daily data. In the various specifications we also include some control variables: the three Fama and French factors (*Market*, *HML* and *SMB*), the riskless rate (i.e., T-Bill rate), the return on the stock, the volatility of the stock, and the logarithm of its volume. These account for market-wide variations (the former) and stock-specific characteristics (the latter) changing with daily frequency. The Fama and French factors, as well as the riskless rate, are downloaded from K. French's web page. The returns on the stocks are derived from the daily CRSP files.

We proceed as follows. First, we test the restrictions that link the fraction of disposition investors to stock return, volatility, turnover and trading volume. Then, we look at the implication of such a relationship at the aggregate level. That is, we study whether the impact of the disposition effect aggregates at the overall market level.

5 The impact of the disposition effect at the stock level

5.1 Disposition effect and stock return, volatility, turnover and trading volume

We begin by examining the impact of the disposition effect on stock return, volatility, turnover and trading volume, by carrying out the analysis at the stock level. We alternatively regress return, volatility, turnover and trading volume on our disposition proxy and a set of control variables. The generic functional form that we estimate is:

$$Z_{it} = \alpha + \beta W_{it} + \gamma C_{it} + \varepsilon_{it}, \qquad (7)$$

where W_{it} is our disposition proxy, $\boldsymbol{C_{it}}$ is a vector of control variables and Z_{it} is the dependent variable that, in the different specifications, will be, alternatively, stock return, return volatility, turnover and trading volume. The broadest set of control variables contains: the daily values of the Fama and French factors (Market, HML, SMB), the riskless rate, company size, overall market volume, stock price and volume. We recall that, from equation 3), theory would require $\beta < 0$ in the case of return and volatility. As a robustness check, we report two alternative specifications that differ for whether the

stock price has been included (Specification I), or not (Specification II), among the control variables.

Also, we consider alternative minimum units of analysis, by grouping stocks in portfolios. We adopt three groupings: the first based on individual stocks and the other two based on 10 portfolios of 10 stocks each, and 5 portfolios of 20 stocks each. In the case of portfolios, the values of the variables (e.g., trading volume) are their average values across the stocks in the portfolios. For example, in the case of the 20-stock portfolio and trading volume, the dependent variable is the average trading volume for the 20 stocks in the portfolio for that day. The portfolio-specific characteristics in the set of independent variables are likewise the average on that day of these characteristics (e.g., company size) for the 20 stocks comprising the portfolio. The disposition variable is the average ratio calculated for those specific stocks in the portfolio. Grouping stocks in portfolios allows us to average out stock-specific idiosyncratic shocks and to see whether the difference between portfolios is related to our variable of interest.

The results are reported in Table 2. They show a significant correlation between our disposition proxy and volatility, return, turnover and trading volume. The correlation is always negative, as theory requires. These findings hold both at the stock level (columns 1-2) and at the portfolio level (columns 3-6). They are also robust to the inclusion of the control variables and to the change of the disposition-based factors. Moreover, the results are consistent whether we identify the disposition investors using daily trades (Identification I) or monthly trades (Identification II).

These results are not only statistically significant, but also economically significant. An increase of our disposition proxy – i.e., the standardized difference between disposition investors and other investors – of one standard deviation reduces stock return by 7 bps a day or 1.56 times the average daily return.

As we mentioned before, given that investors are defined as disposition prone on the basis of their willingness to hold on to the losing stocks, there should not be any direct relationship between their definition and volatility. Therefore, the robust negative relation between volatility and our disposition proxy provides an important evidence in favor of our working hypothesis, suggesting that are results on returns are not a result of reverse causality.

Finally, it is important to note that the disposition proxy is effectively explaining the residual component of the time-series of returns to portfolios and stocks. This is consistent with the hypothesis that trade between disposition investors and their counter-parties affects relative prices. As such, it could be a "style" effect of the sort modeled in Barberis and Shleifer (2002), for example.

5.2 Additional robustness checks

Are these effects just the result of a spurious correlation, due to the way in which we identified our disposition proxies? This is an important issue and we will therefore devote the next section to it.

5.2.1 The disposition effect defined out-of-sample

We start by considering an alternative way of identifying the disposition investors. As we mentioned in Section 4.2, we have identified the disposition investors in an alternative way: out-of-sample, based on the trades of the investors in the previous month. The use of the out-of-sample methodology to identify the disposition investors allows us to control for the possibility of spurious correlation due, for instance, to short-term momentum or mean reversion. Indeed, there is no reason why the criterion of identification – based on prior month trades and on reference prices dating back even longer – be spuriously related to the current market prices.

We consider the impact of the disposition proxy on volatility, return, turnover and trading volume. The functional form, the alternative specifications and the definition of the variables are the same as in Section 5.1. We also consider alternative groupings of stocks in portfolios.

The results are reported in Table 3. They show a negative and statistically significant correlation between our disposition proxy and stock return, volatility, turnover and trading volume. These results are robust across alternative specifications and for different groupings of the stocks into portfolios. These findings support our previous findings and show that they are robust to the way we identify the disposition investors. This suggests that, at the stock level, the disposition effect does indeed affect the stocks in line with what predicted by theory.

5.2.2 Alternative definitions of the disposition effect

We also consider different disposition proxies. As discussed in Section 4, we use two alternative disposition proxies based on purchases ($W_{p,}$) and on net purchases (W_{ps}). We consider the impact of the disposition proxy on volatility, return, turnover and trading volume. The functional form, the alternative specifications and the definition of the variables are the same as in Section 5.1. We also consider alternative groupings of stocks in portfolios.

The results are reported in Table 4. In Panel A, we report the results for the proxy based on purchase, while in Panel B, we report the results for the proxy based on net purchases. Also in this case, the results show a negative and statistically significant correlation between our disposition proxy and stock return, volatility, turnover and trading volume. These findings are robust across alternative specifications and for different groupings of the stocks into portfolios. They are consistent with both the main findings and the previous robustness checks.

Also in this case, the robust negative relation between volatility and our disposition proxy provides important evidence in favor of our working hypothesis. Indeed, we defined investors as disposition prone on the basis of their willingness to hold on to the losing stocks in the previous month. It is unlikely that spurious correlation or reverse causality would induce them to behave in a way that their representation in the market is negatively related to volatility. This supports Grinblatt and Han's theory and shows that our evidence is robust to the way we identify the disposition investors.

5.2.3 Alternative econometric methodology

Finally, as an additional check, we adopt a different econometric approach to estimate equation 7), based on the Fama MacBeth methodology. That is, we run a series of daily cross-sections (at the individual stock level or based on 10 or 5 portfolios) on our disposition proxy and the stock-specific control variables, as defined in Section 5.1. Then, we calculate the mean and statistical significance of the estimated coefficients across the cross-sections. This methodology, being based on a series of cross-sections,

does not exploit the time-series dimension, but is more robust to spurious correlation due to trends or non-stationarity.[12]

We consider both our main disposition proxy (W) and the alternative ones (W_p and W_{ps}). Moreover, as in the previous cases, we consider alternative specifications. In particular, we consider two alternative specifications that differ for whether the stock price has been included (Specification I) on not (Specification II) among the control variables. We also consider alternative groupings of the stocks in portfolios.

The results are displayed in Table 5. In Panel A, we report the results for the proxy based on purchase, in Panel B, we report the results for the proxy based on sales and in Panel C, we report the results for the proxy based on net purchases. We display both the value of the coefficient of interest (β) as well as the average adjusted R^2 of the second stage of the procedure. Again, we find a negative and statistically significant correlation between our disposition proxy and stock return, volatility, turnover and trading volume. These findings are robust across specifications.

Thus far, the results support the Grinblatt and Han (2002) model. The next step is to see whether the disposition effect is a stock specific characteristic or does aggregate at the market level.

6 Does the impact of the disposition effect aggregate at the market level?

6.1 The aggregate disposition effect and market variables

We now move on to see whether the disposition effect aggregates at the market level. It is not implausible that demand shocks by disposition investors might be related to market variables – even prices – at the individual level, or even at the level of small portfolios. If they were only security-specific, however, these effects would cancel each other out at a higher level of aggregation.

Therefore, we start by considering whether a disposition proxy constructed as the aggregation of the different stock-specific proxies affects stocks. This measure is constructed by aggregating across all the 100 stocks the trades of the different classes of

[12] It is worth noting that by constructing our disposition proxy as a standardized (by the overall trade) difference, we do not have a problem of non-stationarity for it.

investors, and then using them to build an aggregated measure. At this level, the results depend upon the tendency of disposition investors to trade in the same direction on a given day – otherwise we would expect little variation in the series and no explanatory power.

We take a two-pronged approach. First, we perform our analysis at the individual stock level. Then, we perform the analysis at the aggregated market level. That is, we calculate the average return, volatility, turnover and trading volume, for all the stocks under consideration, effectively constructing a 100 stock portfolio. Then, we relate this portfolio to our aggregated disposition proxy. For the return regression, for example, we explain the daily time-series of the equal-weighted return index across 100 stocks by the aggregate disposition variable and a variety of controls.

The specifications and the econometric methodology are the same as our base one described in Section 5.1. We use the same set of explanatory and control variables. In the case of the second specification, the stock-specific control variables have been aggregated, by averaging them out for all the stocks in the portfolio.[13]

The results are displayed in Table 6. In Panel A, we report the results for the specification estimated at the individual stock level and in Panel B, we report the results for the specification estimated at the aggregated level, i.e., the 100 stock portfolio. For brevity we focus on our main disposition proxy (*W*).

The results are similar to the ones based on the stock-specific proxy. They show a significant negative correlation between return, volatility, turnover and trading volume and the aggregated disposition proxy. These findings are robust across the different specifications and for the different ways of constructing the disposition proxy. Moreover, these results carry through at the market level, even if they are less significant for trading volume. Thus, not only does disposition matter at the *individual* security level, but also the aggregate behavior of disposition investors appears to matter at the *aggregate* level, suggesting that behavioral effects might be important at the market-wide level.

These results hint at the possibility that the disposition effect has a market-wide impact. In particular, it is important to note that stock returns are affected by a market-

[13] Note that, in this case, we have to remove the market factor from the specification, since the dependent variable is almost perfectly correlated to the S&P 500 index itself.

wide disposition effect. An increase in the aggregate disposition variable reduces stock returns by 12 bps a day or 1.3 times the average daily return. The relationship between returns and the disposition effect we uncovered at the individual stock level in Section 5.1 is consistent with the disposition proxy being a characteristic of individual stocks, either due to fundamentals or the style preferences. The results on the aggregate market we uncovered in this section are, instead, consistent with the disposition effect being an aggregated risk factor on which all the stocks load. The latter seems a priced factor. These explanations of course are not mutually exclusive. Indeed, as indicated in equation 1), stock returns are a function of two components, a backward-looking component related to the price reference (R_t), and a component that accounts for the fundamentals (F_t). Only the latter should be priced, as it is a function of the shocks (innovations) to the fundamentals, while the former only relates to past shocks.

If the percentage of the disposition-prone transactions in each company were not stochastic, we would expect it to affect stock returns by merely amplifying the shocks to the fundamentals. If, on the contrary, the percentage of the disposition-prone transactions changes over time, the change in their relative representation in the markets becomes a factor itself. In this case, it may be priced. In order to distinguish these two possibilities, we turn to tests of *pricing*.

6.2 Is there a common disposition factor?

The availability of just six years of data does not allow us to draw definite conclusions along the pricing dimension. However, we can assess whether stock returns *co-move with a market-wide factor that mimics the disposition effect*. To provide some evidence along this line, we perform a standard asset pricing Fama and MacBeth [FM] two-stage time-series cross-section test, applied to daily returns.

As preliminary evidence, we compute the differential return due to the disposition effect and assess its statistical significance. We follow standard techniques and estimate the alphas constructed by regressing the difference between the returns of high-disposition portfolios and low-disposition portfolios on a constant and risk factors. We consider two alternative specifications: in the first one ("CAPM") the market factor is the return on the market, while in the second one ("three factors"), the factors are the three

Fama and French factors (market, HML and SMB). The disposition portfolios are constructed by ranking stocks on the basis of the value of the disposition proxy for each stock, and then averaging the returns of all the stocks that have a similar level of disposition proxy. We consider three alternative portfolios: the top (bottom) 10%, 20% and 30%. For example, the top (bottom) 10% portfolio contains the average return of all the stocks that rank among the top (bottom) 10% in terms of the value of the disposition proxy. The disposition portfolios are constructed daily. We use both our main disposition proxy (W) and the two alternative ones (W_p and W_{ps}). The returns in the portfolios are the average of the returns of all the stocks in the portfolio. We consider both the equally-weighted and the value-weighted averages.

The results are reported in Table 7. They show that on average the high-disposition portfolios underperform the low-disposition ones. This holds for any classification – differences between the top and bottom 10%, differences between top and bottom 20% and differences between top and bottom 30%. It is also robust to the way we construct our disposition proxy. The results are not only statistically significant, but also economically significant. The disposition effect seems to affect returns by an average of 10 basis points (with a minimum impact of 10 bps and a maximum impact of 50 bps).

We now test for the existence of a common disposition factor. We follow two approaches: first we use individual stock returns and then size-sorted portfolios. In order to construct the disposition factors, we proceed as follows. Once the daily trades and the different classes of investors have been identified, and our disposition proxy constructed, we build portfolios based on them, following the Fama and French (1993) procedure. That is, we rank stocks on the basis of the disposition proxy and then construct return-based factors defined the differences between the returns of the portfolios constructed from high-disposition stocks and the portfolios constructed from low-disposition stocks. These factors are constructed daily.

We apply the FM procedure on rolling intervals and daily updated betas. We consider 20-day rolling windows. This generates sets of betas that are then used as explanatory variables in the second step of the procedure. We use the three Fama and French factors and our disposition factors. The first step of the procedure generates the

βs. These are estimated via a time-series regression. Then, the βs are used in a second-pass regression along the lines of Fama and MacBeth.

At this stage we also include some "characteristics" (c.f. Brennan, Chordia and Subrahmanyam, 1998). These are the *volatility of the stock*, the *logarithm of turnover of the stock* and the *logarithm of its volume*. In the case of portfolios, the characteristics are aggregated for each size-sorted portfolio. We consider alternative specifications based on a different number of factors and characteristics. We also consider the cases with different disposition factors. In order to overcome the potential problems of lead-lag effects due to asynchronous trading with daily data, we apply a Dimson-Marsh correction. We use two alternative specifications: in the first specification, we use 3 days of leads and lags, while in the second, we use five days of leads and lags.

Our disposition factor acts as proxy for the aggregate level of the disposition effect. It increases as the representation of disposition investors in the market rises. As mentioned in Section 2, we expect a negative value of the coefficient on the disposition loading – i.e., the disposition factor to be a discount.

The results are reported in Tables 8 and 9. They provide some evidence in favor of a common disposition factor – at least over this limited six-year time interval. The regressions in Table 8 are estimated at the individual security level, while the regressions in Table 9 are estimated at the portfolio level. The first thing to note is that our disposition factor spreads returns nicely. On the other hand, characteristics like turnover and volatility provide additional explanatory power, beyond the factor used to create portfolios. Moreover, the disposition factor is always strongly significant and negative, in line with the previous findings. These results hold across all the specifications, regardless of the number of additional factors (1 or 3 factor model) and characteristics (volume, volatility, turnover) that are included.

This suggests that not only does the disposition bias of investors appear to affect the returns of the companies in which they trade, but also the exposure of a stock to the aggregate percentage of disposition investors in the market is associated with lower *ex post* returns. These findings support our hypothesis that an increase in the fraction of disposition investors in the market, reduces price pressure and lowers *ex-post* returns.

6.3 A liquidity-based explanation?

What is the economic intuition behind these findings? One explanation could be related to liquidity. That is, the disposition effect, by reducing the stock reaction to fundamental shocks (ε_{Ft}), should also increase market liquidity and therefore reduce the required rate of return on the stock. At the same time, however, we have seen that there is a negative correlation between our disposition proxy – both at the stock specific level and at the aggregate market level – and stock turnover and trading volume. Given that these variables have been considered as proxies for liquidity (Amihud and Mendelson, 1986, Brennan *et al*., 1998), this would suggest that the disposition effect reduces liquidity. To address this issue, we consider the measure of liquidity based on the "illiquidity ratio" of Amihud (2002). The illiquidity ratio at day *t* is defined as:

$$ILLIQ_t = \frac{|Ret_t|}{V_t P_t}, \tag{8}$$

where Ret_t is the stock return during day *t,* and V_tP_t its dollar volume in millions of dollars. This variable represents the percentage price response to a certain trading volume. Amihud (2002) shows that it is positively related to high-frequency measures of price impact and fixed trading costs over the time period for which microstructure data are available. Hasbrouck (2003) shows that this measure is strongly correlated with a high-frequency estimate of liquidity, and considers it as the "the most reliable proxy relationship". The inverse of $ILLIQ_t$ is our measure of liquidity.

Using the definitions of Ret_t, V_t, and P_t reported in Section 2, it can be shown that an increase in the proportion of the disposition investors (μ) affects liquidity depending on the size of μ itself. For low values, an increase of μ increases liquidity. For higher levels, an increase of μ reduces liquidity. The intuition is simple. As the fraction of disposition investors in the market increases, the stock sensitivity to shocks decreases. For low levels of μ, an increase in μ raises trading volume and reduces returns. The two effects re-enforce each other to increase liquidity (i.e., the numerator of $ILLIQ_t$ decreases and the denominator increases). However, for higher values of μ, an increase in μ decreases trading volume. This effect more than offsets the decrease in return, reducing liquidity.

Is this reflected in the data? We analyze whether the disposition effect affects liquidity, both at the individual stock level and at the aggregate market level. We regress liquidity on the disposition proxy and control variables. The definition of disposition proxies and the econometric specification are the same as in the previous sections. We first consider the case in which, for each stock, we regress its liquidity on the disposition proxy defined at the stock level and control variables. The findings are reported in Table 10, Panels A, B and C, respectively for the alternative disposition proxies (i.e., W_p, W and W_{ps}).

All the findings agree and show that the degree of liquidity of each stock is negatively related to the fraction of disposition investors who trade it. These results hold both at the stock level (columns 1-2) and at the aggregate level (columns 3-6). They are also robust to the inclusion of the control variables (Specification I and II) and to the change of the disposition proxy.

We also focus on the case in which the disposition proxies have been aggregated across all the stocks. We consider two alternative cases: in the first one ("Aggregate 1"), we regress stock liquidity on the aggregate value of our disposition proxies and control variables defined as in Table 2. In the second case ("Aggregate 2"), we regress the aggregate (average) value of liquidity on the aggregate value of our disposition proxies and the aggregate (average) value of the control variables. The first specification is reported in Panel D and the second specification is displayed in Panel E. The findings in Panel D confirm the previous ones. However, if we look at the market level (Panel E), we see that the impact of the disposition effect is not significant. Overall, these findings suggest that higher liquidity can hardly be an explanation of the lower returns. Indeed, unlike what the theory predicts, the data suggest that lower stock returns would be related to a reduction in liquidity.

Conclusion

Measuring the impact of behavioral biases on asset prices is difficult because econometricians rarely have access to individual investor decisions. Ultimately, tests of the relevance of behavioral finance must be conducted jointly on behavioral data and asset data. In this study, we consider the widely documented disposition effect. We

construct a variable – based on investor trades – that acts as proxy for the representation of disposition-prone investors in the market and test how it relates to stock return, volatility and trading volume. We confirm the theoretical predictions of the model of Grinblatt and Han (2002) reporting a strong negative correlation between the disposition effect and stock return, volatility and trading volume.

We also show that the disposition effect is not only stock-specific, but aggregates at the market level, forming a factor that affects returns, volatility and trading volume. This generates a common price-relevant factor that spreads stock returns. The exposure of a stock to this disposition factor is associated with lower *ex post* returns.

This study has further implications for volatility studies and micro-structure effects. We find evidence that both trading volume (i.e., turnover) and volatility may depend in general upon the composition of the market, and more specifically on disposition investors.

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Table 1: Descriptive Statistics

We report descriptive statistics of the dataset. In Panel A, we report descriptive statistics for groups of accounts broken down on the basis of the average number of transactions they enact each year (n). We consider 5 classes of accounts: the ones with less than 5 transactions, the accounts with less than 10 and more than 5 transactions, the accounts with less than 15 and more than 10 transactions, the accounts with less than 20 and more than 15 transactions and the accounts with more than 20 transactions. For each group we the number of accounts, the number of transactions and the percentage (out of the total transactions) of purchases and sales. For each group we also report the average running balance Running Balance and the Turnover Ratio. The Running Balance is constructed as the average holdings standardized by the amount of time they are held. Turnover is calculated as the sum of absolute value of purchases and absolute value of sales (expressed in terms of number of shares) divided by the average running balance. In Panel B, we report some "disposition characteristics" of the accounts. That is, for each group we separately report the buy-on-gains, buy-on-loss, sell-on-gain and sell-on-loss transactions, as described in the text in the Section on Data Construction. For each of these categories of transactions, we report the number of transactions and their percentage in terms of overall transactions.

Panel A

		Number of Transactions (n)				
		n<5	*5<n<10*	*10<n<15*	*15<n<20*	*20<n*
Number of Accounts		44482	21303	11159	6844	23139
Number of Transactions (Total)		94461	142796	131527	115297	1427938
Percentage of Purchases		55.10	54.42	54.67	54.64	55.07
Percentage of Sales		44.90	45.58	45.33	45.36	44.93
Running Balance	Mean	558	599	598	682	950
(in number of shares)	Median	167	200	200	220	400
	S.Dev	87522	95686	66081	74931	92067
Turnover Ratio	Mean	1.748	4.055	6.737	9.352	30.470
(in terms of number of shares)	Median	1.200	3.632	6.292	8.834	19.460
	S.Dev	10.233	3.826	4.118	5.4115	65.370

Panel B

	Number of Transactions (n)				
	n<5	*5<n<10*	10<n<15	15<n<20	20<n
Buy-on-gain					
Number of Transactions	1925	5135	5643	5617	132229
Percentage of Total Transactions	2.04	3.60	4.29	4.78	9.26
Sell-on-gain					
Number of Transactions	6713	17934	19992	19410	286110
Percentage of Total Transactions	7.10	12.56	15.20	16.83	20.04
Buy-on-loss					
Number of Transactions	3076	8254	8931	9045	179788
Percentage of Total Transactions	3.26	5.78	6.79	7.84	12.59
Sell-on-loss					
Number of Transactions	4430	11424	12615	12714	202789
Percentage of Total Transactions	4.69	8.00	9.59	11.02	14.20

Tables 2: The Disposition Proxy and the Stocks

We report the estimates of the regression of stock volatility, return, turnover and trading volume on our disposition proxy and a set of control variables. For each stock we construct volatility as the logarithm of the difference between the highest price of the day minus the lowest price of the day. We use the logarithm of turnover as measure of trading volume. This is defined as trading volume (measured by the number of shares traded) divided by the outstanding number of shares. Our disposition proxy (*W*) is constructed as the ratio between sell-at-loss minus sell-at-gain standardized by the sum of sell-at-loss and sell-at-gain. This variable has been divided by 1,000. The control variables include: the daily values of the Fama and French factors (Market, HML, SMB), the riskless rate, company size, the logarithm of the average market volume and stock price price, overall market volatility, company and time specific constants. To estimate equation 7), we adopt a pooled estimation with a robust variance-covariance matrix. We consider two alternative specifications that differ for whether the overall market volatility and time and company dummy have been included (Specification I) on not (Specification II) among the control variables. We also consider alternative grouping of the stocks in portfolios. We adopt three groupings: the first based on individual stocks and the other two based on 10 portfolios of 10 stocks each and 5 portfolios of 20 stocks each. In the case of portfolios, the values of the variables are their average values across the stocks in the portfolios. The frequency is daily.

Specifications

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
Variables	*I*		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-20.68	-27.53	-22.64	-28.77	-7.75	-5.82	-12.59	-7.41	-9.62	-8.00	-13.87	-9.99
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.35		0.31		0.63		0.38		0.51		0.35	
Obs	149600		149600		14960		14960		7480		7480	
Return												
Disp. Proxy	-1.34	-31.38	-1.34	-31.26	-0.57	-9.22	-0.59	-9.18	-0.78	-13.78	-0.79	-13.73
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.18		0.18		0.67		0.65		0.51		0.49	
Obs	149600		149600		14960		14960		7480		7480	
Turnover												
Disp. Proxy	-69.76	-34.84	-71.65	-35.71	-7.68	-2.04	-10.94	-2.81	-18.20	-5.79	-20.32	-6.35
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.14		0.14		0.32		0.28		0.24		0.20	
Obs	149600		149600		14960		14960		7480		7480	
Volume												
Disp. Proxy	-84.21	-36.61	-85.10	-36.93	-26.03	-5.51	-24.61	-5.15	-30.75	-6.81	-34.88	-7.78
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.41		0.41		0.70		0.69		0.57		0.57	
Obs	149600		149600		14960		14960		7480		7480	

Table 3: Alternative ways of identifying the disposition investors I

We report the estimates of the regression of stock volatility, return, turnover and trading volume on our disposition proxy and a set of control variables. All the variables and the econometric specification are the same as in Table 2. The way of identifying the disposition investors is different. Disposition investors are identified out-of-sample. That is, first, we define as disposition-prone the investors who, in a month, have "sold winners and held on to losers" in a systematic way and then we trace their behavior in the following month. We follow the same methodology developed by Odean (1998). For each investor, we focus on his *realized* gains/losses and his *paper* gains/losses. We consider all the stocks in which the investor trades and not only the 100 stocks on which we will focus our analysis. Each day, we identify for each investor his *realized* gains/losses. These are constructed by comparing the selling price for each stock sold to its purchase price. We define as purchase price the one based on the LIFO methodology before described. For all the other stocks that are in the portfolio and are not sold, we also construct the daily *paper* gain/losses by comparing the purchase price of each stock (i.e., the price at which it is held in the portfolio) to the stock's high and low price for that day. If both the daily high and low are above the purchase price, this is counted as a paper gain; if they are both below it is counted as a paper loss; if its purchase price lies between the high and the low, neither a gain nor loss is counted. For each day, all the paper gains/losses for a particular stock are accumulated as well as the realized gains/losses. Then, gains/losses are aggregated at the end of the month and for each investor the ratio of realized gains to total gains (PGR) and the ratio of realized losses to total losses (PLR) are constructed. Then, we define as disposition-prone the investors the investors for which PGR > PLR. The classification is done for each month. Then, we trace the trades of the different classes of investors in the following month. The following month, each day, we use the trades of the disposition investors (identified as such the previous month) to construct the fraction of disposition investors over the total investors in the market for the particular stock in the specific day. This is our disposition proxy.

Specifications

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variables	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-2.85	-2.59	-3.44	-2.99	-3.49	-3.05	-6.74	-4.53	-3.00	-2.49	-5.46	-3.88
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.34		0.31		0.63		0.38		0.51		0.35	
Obs	149600		149600		14960		14960		7480		7480	
Return												
Disp. Proxy	-0.36	-5.61	-0.36	-5.54	-0.14	-2.50	-0.12	-2.15	-0.25	-4.15	-0.24	-3.87
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.18		0.17		0.67		0.65		0.51		0.49	
Obs	149600		149600		14960		14960		7480		7480	
Turnover												
Disp. Proxy	-12.53	-4.23	-13.14	-4.42	-14.95	-4.64	-17.23	-5.18	-11.71	-3.68	-13.38	-4.12
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.14		0.13		0.32		0.28		0.24		0.20	
Obs	149600		149600		14960		14960		7480		7480	
Volume												
Disp. Proxy	-14.76	-4.37	-14.97	-4.43	-17.36	-3.38	-22.60	-4.13	-14.59	-2.92	-17.59	-3.41
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.37		0.37		0.54		0.47		0.46		0.42	
Obs	149600		149600		14960		14960		7480		7480	

Table 4: Alternative ways of identifying the disposition investors II

We report the estimates of the regression of stock volatility, return, turnover and trading volume on our disposition proxy and a set of control variables. All the variables and the econometric specification are the same as in Table 2. The way of identifying the disposition investors is different. We consider two alternative disposition proxies: W_p and W_{ps}. W_p is constructed as the ratio between buy-at-loss minus buy-at-gain standardized by the sum of buy-at-loss and buy-at-gain. W_{ps} is constructed as the ratio between buy-at-loss plus sell-at-loss minus sell-at-gain minus buy-at-gain standardized by the sum of buy-at-loss, buy-at-gain, sell-at-loss and sell-at-gain. Both W_p and W_{ps} have been divided by 1,000. In Panel A and B, we report, respectively, the results for $W_{p,}$ and W_{ps}.

Panel A: W_p

	Specifications											
	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variables	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-12.92	-14.10	-14.24	-14.85	-6.34	-5.29	-10.95	-7.10	-10.23	-8.70	-13.85	-10.11
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.34		0.31		0.63		0.38		0.51		0.35	
Obs	149600		149600		14960		14960		7480		7480	
Return												
Disp. Proxy	-0.78	-14.95	-0.78	-14.91	-0.38	-6.75	-0.39	-6.69	-0.53	-9.29	-0.53	-9.08
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.18		0.17		0.67		0.65		0.51		0.49	
Obs	149600		149600		14960		14960		7480		7480	
Turnover												
Disp. Proxy	-8.76	-3.56	-9.86	-3.99	-5.23	-1.56	-8.60	-2.48	-4.17	-1.35	-6.26	-1.99
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.14		0.13		0.32		0.28		0.24		0.20	
Obs	149600		149600		14960		14960		7480		7480	
Volume												
Disp. Proxy	2.02	0.72	-2.20	-2.30	-11.19	-2.65	-11.69	-2.72	3.58	1.84	0.11	0.02
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.40		0.40		0.70		0.69		0.57		0.56	
Obs	149600		149600		14960		14960		7480		7480	

Panel B: W_{ps}

Variables	*Specifications*											
	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-16.56	-25.03	-18.19	-26.22	-7.55	-5.30	-12.05	-6.70	-10.71	-8.51	-14.20	-9.88
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.35		0.31		0.63		0.38		0.51		0.35	
Obs	149600		149600		14960		14960		7480		7480	
Return												
Disp. Proxy	-1.18	-31.88	-1.18	-31.77	-0.75	-11.52	-0.75	-11.19	-0.88	-15.59	-0.89	-15.50
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.18		0.18		0.67		0.65		0.51		0.49	
Obs	149600		149600		14960		14960		7480		7480	
Turnover												
Disp. Proxy	-42.40	-24.76	-44.02	-25.65	-10.93	-2.46	-11.79	-2.66	-8.74	-2.74	-10.71	-3.29
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.14		0.13		0.13		0.12		0.24		0.20	
Obs	149600		149600		14960		14960		7480		7480	
Volume												
Disp. Proxy	-47.71	-24.36	-48.37	-24.65	-20.25	-4.08	-18.43	-3.67	-10.00	-2.21	-13.61	-3.02
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.40		0.40		0.70		0.69		0.57		0.57	
Obs	149600		149600		14960		14960		7480		7480	

Table 5: Alternative econometric specification

We report the estimates of the regression of stock volatility, return, turnover and trading volume on our disposition proxy and a set of control variables. All the variables and the econometric specification are the same as in Table 2. The identification of the disposition investors is the same as in Tables 2 and 4. The econometric methodology is based on the Fama MacBeth methodology. That is, we run a series of daily cross-sections (based on the 100 stocks or 10 or 5 portfolios) on our disposition proxy and the stock-specific control variables and then we calculate the mean and statistical significance of the estimated coefficients across the cross-sections. In both specifications we report only the coefficients and the statistics for the disposition proxy. We consider two alternative specifications that differ for whether company price has been included (Specification I) or not (Specification II) among the control variables. We also consider alternative grouping of the stocks in portfolios. *AveAdjR*^{2}is the average of the Adjusted R^2 of the second stage.

	Specifications											
	Single Stocks				*10 Portfolios*				*5 Portfolios*			
Variables	*I*		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Panel A: W_p												
Disp. Proxy	-29.58	-41.53	-26.52	-37.92	-9.80	-6.41	-9.19	-6.56	-12.65	-10.60	-12.84	-11.08
AveAdj.R^2	0.09		0.03		0.33		0.31		0.31		0.29	
Panel B: W												
Disp. Proxy	-33.86	-43.02	-35.38	-44.01	-12.02	-6.63	-11.21	-6.75	-10.86	-8.29	-12.70	-9.88
AveAdj.R^2	0.10		0.03		0.32		0.31		0.31		0.29	
Panel C: W_{ps}												
Disp. Proxy	-30.63	-51.43	-30.32	-53.56	-13.52	-7.30	-11.46	-6.58	-13.01	-9.88	-14.45	-11.14
AveAdj.R^2	0.10		0.03		0.32		0.31		0.32		0.29	
Return												
Panel A: W_p												
Disp. Proxy	-2.53	-63.75	-2.51	-61.81	-0.30	-3.06	-0.37	-4.48	-0.54	-8.09	-0.57	-8.67
AveAdj.R^2	0.01		0.01		0.03		-0.01		0.03		0.01	
Panel B: W												
Disp. Proxy	-3.98	-61.57	-4.05	-59.65	-0.65	-5.82	-0.72	-6.70	-0.79	-10.45	-0.85	-11.61
AveAdj.R^2	0.01		0.01		0.04		0.01		0.04		0.01	
Panel C: W_{ps}												
Disp. Proxy	-3.52	-72.51	-3.56	-69.39	-0.81	-7.39	-0.89	-8.72	-0.93	-12.35	-1.00	-13.51
AveAdj.R^2	0.01		0.01		0.04		0.01		0.04		0.01	

Turnover

Panel A: W_p

Disp. Proxy	-56.61	-46.05	-46.84	-33.03	-7.10	-2.78	-12.57	-3.69	-10.76	-6.06	-15.62	-5.74
AveAdj.R^2	0.68		0.59		0.69		0.42		0.76		0.38	

Panel B: W

Disp. Proxy	-48.71	-27.43	-70.68	-37.52	3.06	0.83	-8.28	-1.84	-1.92	-0.97	-13.93	-4.65
AveAdj.R^2	0.68		0.59		0.70		0.43		0.76		0.38	

Panel C: W_{ps}

Disp. Proxy	-51.00	-44.17	-60.62	-43.87	2.14	0.62	-0.24	-5.00	-4.67	-4.67	-16.73	-5.55
AveAdj.R^2	0.68		0.59		0.70		0.43		0.76		0.38	

Volume

Panel A: W_p

Disp. Proxy	60.65	29.81	64.41	29.83	-25.71	-3.97	-16.07	-2.75	2.86	0.57	1.46	0.29
AveAdj.R^2	0.49		0.11		0.69		0.71		0.60		0.58	

Panel B: W

Disp. Proxy	-165.78	-47.45	-192.16	-55.15	-21.21	-2.45	-16.85	-2.39	-30.44	-5.60	-37.02	-7.01
AveAdj.R^2	0.49		0.12		0.69		0.71		0.60		0.59	

Panel C: W_{ps}

Disp. Proxy	-77.51	-29.45	-91.66	-35.07	-32.58	-3.93	-16.81	-2.28	-11.37	-2.04	-2.48	-2.27
AveAdj.R^2	0.49		0.12		0.70		0.71		0.61		0.59	

Table 6: Disposition Index and Market Variables

We report the estimates of the regression of the volatility, return, turnover and trading volume on the aggregate value of our disposition proxies. The definition of disposition proxies and the econometric specification are the same as in the previous tables. The disposition proxies have been aggregated across all the stocks. We consider two specifications: the first one regresses volatility, return, turnover and trading volume of each stock on the aggregate value of our disposition proxies and control variables defined as in Table 2. The second specification regresses the aggregate (average) value of volatility, return, turnover and trading volume on the aggregate value of our disposition proxies and the aggregate (average) value of the control variables. The first specification is reported in Panel A and the second specification in Panel B.

Panel A: Individual Stocks and Common Factors

	Specifications											
	Factor W_p				*Factor W*				*Factor W_{ps}*			
Variables	*I*		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-22.60	-9.78	-26.41	-11.89	-9.97	-4.02	-11.83	-4.75	-22.19	-7.88	-26.05	-9.58
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.16		0.06		0.16		0.05		0.16		0.05	
Obs	145300		145300		145300		145300		145300		145300	
Return												
Disp. Proxy	-1.44	-13.14	-1.44	-13.19	-0.20	-1.65	-0.21	-1.68	-1.13	-8.33	-1.13	-8.38
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.08		0.08		0.08		0.08		0.08		0.08	
Obs	145300		145300		145300		145300		145300		145300	
Turnover												
Disp. Proxy	-67.05	-12.30	-67.05	-12.30	-77.13	-12.86	-77.13	-12.86	-77.01	-12.84	-108.09	-16.35
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.0300		0.0300		0.0300		0.0300		0.0300		0.0300	
Obs	145300		145300		145300		145300		145300		145300	
Volume												
Disp. Proxy	-48.58	-7.42	-38.82	-5.97	-55.59	-7.83	-50.11	-6.98	-87.04	-10.94	-76.74	-9.74
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.24		0.17		0.24		0.17		0.24		0.17	
Obs	145300		145300		145300		145300		145300		145300	

Panel B: The Market and Common Factors

Variables	*Specifications*											
	Factor W_p				*Factor W*				*Factor W_{ps}*			
	I		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Volatility												
Disp. Proxy	-29.21	-4.21	-30.61	-4.40	-30.23	-3.99	-30.56	-4.01	-41.43	-4.92	-42.52	-5.02
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.19		0.18		0.18		0.18		0.19		0.18	
Obs	1496		1496		1496		1496		1496		1496	
Return												
Disp. Proxy	-3.42	-9.93	-3.43	-9.96	-4.35	-9.92	-4.35	-9.93	-5.66	-12.95	-5.66	-12.99
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.46		0.46		0.48		0.48		0.50		0.50	
Obs	1496		1496		1496		1496		1496		1496	
Turnover												
Disp. Proxy	-37.58	-2.41	-44.30	-2.79	-69.29	-4.11	-70.83	-4.17	-82.34	-4.25	-87.46	-4.47
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.09		0.05		0.09		0.06		0.10		0.06	
Obs	1496		1496		1496		1496		1496		1496	
Volume												
Disp. Proxy	-9.98	-0.56	-20.36	-1.10	-52.60	-2.78	-54.94	-2.87	-55.95	-2.57	-63.82	-2.88
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Adj.R^2	0.44		0.40		0.45		0.41		0.45		0.41	
Obs	1496		1496		1496		1496		1496		1496	

Tables 7: Abnormal returns of Disposition Portfolios

We report the alphas constructed by regressing the difference between the returns of high-disposition portfolios and low-disposition portfolios on a constant and risk factors. We consider two alternative specifications: in the first one ("CAPM") the market factor is the return on the market, while in the second one ("three factors"), the factors are the three Fama and French factors (i.e., market, HML and SMB). The disposition portfolios are constructed by ranking stocks on the basis of the value of the disposition proxy for each stock and then averaging the returns of all the stocks that have similar level of disposition proxy. We consider three alternative types of portfolios: the top (bottom) 10%, 20% and 30%. For example, the top (bottom) 10% portfolio contains the average return of all the stocks that rank among the top 10% in terms of the value of the disposition proxy. The disposition portfolios are constructed daily. We consider our main disposition proxy (W) and the two alternative ones (W_p and W_{ps}). The returns in the portfolios are the average of the returns of all the stocks of the portfolio. We consider both the equally weighed and the value weighed averages.

	Specifications											
	Top 10%-Bottom 10%				*Top 20%-Bottom 20%*				*Top 30%-Bottom 30%*			
Variables	*I*		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Equally Weighed												
W_p												
CAPM	-0.002	-11.56	-	-	-0.001	-11.34	-	-	-0.001	-9.63	-	-
Three Factors	-	-	-0.002	-11.34	-	-	-0.002	-11.29	-	-	-0.001	-9.63
W												
CAPM	-0.005	-23.55	-	-	-0.003	-21.94	-	-	-0.002	-20.01	-	-
Three Factors	-	-	-0.005	-23.35	-	-	-0.003	-21.81	-	-	-0.003	-20.06
W_{ps}												
CAPM	-0.0050	-23.62	-	-	-0.003	-23.73	-	-	-0.002	-22.03	-	-
Three Factors	-	-	-0.005	-23.61	-	-	-0.003	-23.77	-	-	-0.003	-22.03
Value Weighed												
W_p												
CAPM	-0.003	-10.989	-	-	-0.0024	-12.09	-	-	-0.001	-11.10	-	-
Three Factors	-	-	-0.003	-10.90	-	-	-0.002	-12.35	-	-	-0.002	-11.46
W												
CAPM	-0.005	-20.42	-	-	-0.0038	-19.64	-	-	-0.002	-18.20	-	-
Three Factors	-	-	-0.005	-20.21	-	-	-0.004	-19.68	-	-	-0.003	-18.63
W_{ps}												
CAPM	-0.005	-20.29	-	-	-0.004	-21.08	-	-	-0.003	-20.15	-	-
Three Factors	-	-	-0.005	-20.08	-	-	-0.004	-20.98	-	-	-0.003	-20.17

Table 8: Fama-MacBeth Regressions: Explaining the Cross-Sections of Individual Stock Returns

The table reports the results of the second stage of a Fama-MacBeth procedure. We use the three Fama and French factors (R_{mkt}, HML, SMB) and our disposition factors. We consider the three disposition proxies: W_p, W and W_{ps} and we construct mimicking portfolios based on them (Fama and French, 1993). These are based on the difference between the return of the portfolio made of the high-factor stocks and the portfolios made of the low-factor stock and then we run the first step of the procedure estimation βs. The factors are defined as F_{Wp}, F_W and F_{Wps} (for W_p, W and W_{ps} respectively). At the second stage f the procedure we also include some "characteristics", such as the volatility on the stock, the logarithm of turnover of the stock and the logarithm of its trading volume. A Dimson-Marsh correction is applied to control for potential lead-lag effects due to asynchronous trading. We consider 2 specifications: in the first one (Panel A) we use 3 days of leads and lags, while in the second one (Panel B) we use 5 days of leads and lags. We consider different specifications with different explanatory variables as well as different disposition variables. The frequency is daily and the procedure is applied at the stock level.

Panel A

Specifications

Disposition Factor F_{Wp}

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wp}	-0.11	-3.34	-0.11	-3.30	-0.9	-2.74	-0.09	-2.71	-0.08	-2.72	-0.073	-2.23
Controls												
R_{mkt}	-0.31	-0.11	-0.43	-0.15	1.75	0.58	1.72	0.58	2.19	0.96	-	-
HML	-1.50	-0.83	-1.45	-0.81	-0.46	-0.24	-0.44	-0.24	-	-	-	-
SMB	1.11	0.68	1.14	0.70	-0.42	-0.23	-0.42	-0.23	-	-	-	-
Volatility	0.001	1.47	0.001	2.59	0.001	0.26	-	-	-	-	-	-
Turnover	0.10	4.60	0.09	5.17	-	-	-	-	-	-	-	-
Volume	-0.01	-0.61	-	-	-	-	-	-	-	-	-	-

Disposition Factor F_W

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_W	-0.22	-6.80	-0.22	-6.67	-0.23	-6.83	-0.23	-6.85	-0.22	-6.80	-0.20	-6.14
Controls												
R_{mkt}	0.17	0.06	-0.02	-0.001	2.13	0.70	2.07	0.69	2.69	1.15	-	-
HML	-1.33	-0.74	-1.25	-0.70	-0.13	-0.06	-0.12	-0.06	-	-	-	-
SMB	1.13	0.69	1.19	0.72	-0.43	-0.24	-0.42	-0.23	-	-	-	-
Volatility	0.001	1.53	0.001	2.97	0.001	0.84	-	-	-	-	-	-
Turnover	0.10	4.64	0.09	5.14	-	-	-	-	-	-	-	-
Volume	-0.01	-0.81	-	-	-	-	-	-	-	-	-	-

Disposition Factor F_{Wps}

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wps}	-0.16	-4.83	-0.15	-4.80	-0.16	-4.82	-0.16	-4.81	-0.14	-4.25	-0.12	-3.46
Controls												
R_{mkt}	0.37	0.13	0.13	0.04	2.23	0.75	2.17	0.74	2.35	1.01	-	-
HML	-1.89	-1.06	-1.71	-0.96	-0.61	-0.32	-0.59	-0.31	-	-	-	-
SMB	0.98	0.61	1.03	0.64	-0.56	-0.31	-0.55	-0.31	-	-	-	-
Volatility	0.001	1.02	0.001	2.85	0.001	0.81	-	-	-	-	-	-
Turnover	0.10	4.54	0.09	4.90	-	-	-	-	-	-	-	-
Volume	-0.01	-1.30	-	-	-	-	-	-	-	-	-	-

Panel B

Specifications

Disposition Factor F_{Wp}

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wp}	-0.09	-3.15	-0.09	-3.14	-0.08	-2.70	-0.08	-2.69	-0.07	-2.56	-0.06	-2.24
Controls												
R_{mkt}	-0.88	-0.52	-0.97	-0.57	1.21	0.67	1.4	0.64	1.63	1.00	-	-
HML	-2.2	-1.78	-2.21	-1.81	-1.15	-0.88	-1.1	-0.83	-	-	-	-
SMB	2.28	1.87	2.30	1.89	0.84	0.65	0.88	0.68	-	-	-	-
Volatility	0.001	2.47	0.001	3.87	-0.001	-0.04	-	-	-	-	-	-
Turnover	0.09	5.48	0.09	6.58	-	-	-	-	-	-	-	-
Volume	0.001	0.06	-	-	-	-	-	-	-	-	-	-

Disposition Factor F_{W}

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{W}	-0.15	-4.96	-0.14	-4.90	-0.15	-4.98	-0.15	-5.01	-0.14	-4.79	-0.12	-4.38
Controls												
R_{mkt}	-0.47	-0.28	-0.57	-0.33	1.57	0.87	1.47	0.83	1.91	1.20	-	-
HML	-2.31	-1.93	-2.31	-1.92	-1.15	-0.90	-1.08	-0.84	-	-	-	-
SMB	2.29	1.86	2.33	1.89	0.90	0.69	0.94	0.73	-	-	-	-
Volatility	0.001	2.57	0.001	4.53	0.001	0.78	-	-	-	-	-	-
Turnover	0.09	5.64	0.09	6.69	-	-	-	-	-	-	-	-
Volume	-0.001	-0.21	-	-	-	-	-	-	-	-	-	-

Disposition Factor F_{Wps}

Variables	*I*		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wps}	-0.12	-4.70	-0.12	-4.70	-0.13	-4.65	-0.13	-4.66	-0.11	-4.20	-0.09	-3.50
Controls												
R_{mkt}	-0.21	-0.12	-0.33	-0.19	1.78	0.99	1.69	0.95	1.97	1.23	-	-
HML	-2.53	-2.09	-2.51	-2.08	-1.38	-1.05	-1.28	-0.98	-	-	-	-
SMB	2.31	1.91	2.35	1.94	0.93	0.72	0.96	0.75	-	-	-	-
Volatility	0.001	2.08	0.001	4.03	0.001	0.59	-	-	-	-	-	-
Turnover	0.09	5.20	0.09	6.26	-	-	-	-	-	-	-	-
Volume	-0.001	-0.18	-	-	-	-	-	-	-	-	-	-

Table 9: Fama-MacBeth Regressions: Explaining the Cross-Sections of Portfolio Returns.

The table reports the results of the second stage of a Fama-MacBeth procedure for 10 *size-sorted* portfolios. We consider the Fama and French factors (R_{mkt}, HML, SMB) and our disposition factors (F_{Wp}, F_W and F_{Wps}) as defined in Table 9. The estimation is the same as in Table 9. The stocks characteristics are averaged for all the stocks in the portfolio. In Panel A, we consider a Dimson correction based on 3 days; in Panel B, a correction based on 5 days.

Panel A

Specifications

Variables	*Disposition Factor F_{Wp}*											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wp}	0.001	0.35	-0.001	-2.05	-0.001	-2.48	-0.001	-2.41	-0.001	-2.06	-0.001	-2.00
Controls												
R_{mkt}	-0.06	-0.95	-0.03	-0.51	-0.008	-0.14	-0.009	-0.14	0.02	0.39	-	-
HML	0.08	1.60	0.09	1.94	0.05	1.53	0.07	1.92	-	-	-	-
SMB	-0.002	-0.05	-0.007	-0.20	-0.02	-0.67	-0.02	-0.70	-	-	-	-
Volatility	0.05	1.77	0.03	1.53	0.05	2.43	-	-	-	-	-	-
Turnover	-0.39	-0.40	0.09	0.10	-	-	-	-	-	-	-	-
Volume	0.05	1.71	-	-	-	-	-	-	-	-	-	-

	Disposition Factor F_W											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_W	-0.002	-2.09	-0.002	-2.52	-0.003	-3.52	-0.002	-4.39	-0.002	-3.14	-0.003	-4.28
Controls												
R_{mkt}	-0.11	-1.79	-0.001	-0.02	0.01	0.37	-0.01	-0.33	0.03	0.65	-	-
HML	0.09	1.80	0.09	1.79	0.03	0.98	0.04	1.12	-	-	-	-
SMB	-0.02	-0.72	-0.04	-1.45	-0.04	-1.30	-0.02	-0.66	-	-	-	-
Volatility	0.01	0.71	0.008	0.37	0.03	1.73	-	-	-	-	-	-
Turnover	1.61	1.18	-0.04	-0.04	-	-	-	-	-	-	-	-
Volume	-0.00	-0.17	-	-	-	-	-	-	-	-	-	-

Variables	*Disposition Factor F_{Wps}*											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wps}	-0.001	-2.10	-0.00	-2.46	-0.001	-3.28	-0.001	-3.26	-0.001	-1.98	-0.002	-2.70
Controls												
R_{mkt}	-0.11	-1.54	-0.02	-0.30	0.03	0.52	0.001	0.10	0.02	0.51	-	-
HML	0.16	2.36	0.113	1.62	0.04	1.08	0.04	1.12	-	-	-	-
SMB	-0.01	-0.25	-0.02	-0.61	-0.02	-0.74	-0.01	-0.42	-	-	-	-
Volatility	0.01	0.26	0.004	0.20	0.04	1.88	-	-	-	-	-	-
Turnover	0.17	0.13	-0.24	-0.21	-	-	-	-	-	-	-	-
Volume	0.00	0.19	-	-	-	-	-	-	-	-	-	-

Panel B

Specifications

Variables	*Disposition Factor F_{Wp}*											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wp}	0.00	0.08	-0.001	-1.86	-0.001	-2.70	-0.001	-2.53	-0.001	-1.87	-0.001	-1.95
Controls												
R_{mkt}	-0.02	-0.41	0.01	0.45	-0.01	-0.25	-0.01	-0.27	0.01	0.35	-	-
HML	0.04	1.08	0.038	1.03	0.02	0.97	0.03	1.23	-	-	-	-
SMB	0.01	0.33	0.006	0.23	-0.007	-0.27	-0.00	-0.17	-	-	-	-
Volatility	0.03	1.58	0.02	1.34	0.04	2.38	-	-	-	-	-	-
Turnover	-0.55	-0.72	0.04	0.07	-	-	-	-	-	-	-	-
Volume	0.02	1.37	-	-	-	-	-	-	-	-	-	-

Variables	*Disposition Factor F_{W}*											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{W}	-0.002	-2.75	-0.001	-1.66	-0.002	-3.007	-0.001	-3.22	-0.001	-2.01	-0.001	-3.22
Controls												
R_{mkt}	-0.03	-0.81	0.03	0.75	0.008	0.22	-0.02	-0.65	0.02	0.77	-	-
HML	0.02	0.55	0.05	1.32	0.009	0.30	0.005	0.17	-	-	-	-
SMB	0.005	0.20	-0.03	-1.23	-0.02	-0.76	0.001	0.03	-	-	-	-
Volatility	0.02	1.57	0.004	0.28	0.03	2.28	-	-	-	-	-	-
Turnover	0.39	0.40	-0.14	-0.16	-	-	-	-	-	-	-	-
Volume	0.02	1.04	-	-	-	-	-	-	-	-	-	-

Variables	*Disposition Factor F_{Wps}*											
	I		*II*		*III*		*IV*		*V*		*VI*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
F_{Wps}	-0.003	-2.35	-0.002	-2.55	-0.002	-3.50	-0.001	-3.88	-0.001	-2.31	-0.001	-2.86
Controls												
R_{mkt}	-0.07	-1.30	0.006	0.12	0.01	0.51	-0.01	-0.38	0.01	0.43	-	-
HML	0.09	1.86	0.05	1.05	0.001	0.28	0.02	0.58	-	-	-	-
SMB	0.01	0.28	-0.002	-0.06	-0.008	-0.28	0.005	0.23	-	-	-	-
Volatility	0.02	0.89	0.01	0.65	0.03	2.02	-	-	-	-	-	-
Turnover	0.15	0.13	0.10	0.13	-	-	-	-	-	-	-	-
Volume	0.01	0.68	-	-	-	-	-	-	-	-	-	-

Table 10: Liquidity and the Disposition Proxy

We report the estimates of the regression of liquidity on our disposition proxy. Liquidity is defined as in equation 8) in the text. The definition of disposition proxies and the econometric specification are the same as in the previous tables. We consider a specification in which for each stock we regress its liquidity on the disposition proxy defined at the stock level and control variables defined as in previous tables. This specification is reported in Panels A, B and C, respectively for W_p, W and W_{ps}. We also consider the case in which the disposition proxies have been aggregated across all the stocks. We consider two specifications: the first one ("Aggregate 1") regresses stock liquidity on the aggregate value of our disposition proxies and control variables defined as in Table 2. The second specification ("Aggregate 2") regresses the aggregate (average) value of liquidity on the aggregate value of our disposition proxies and the aggregate (average) value of the control variables. The first specification is reported in Panel D and the second specification in Panel E. The coefficients have been divided by 1,000,000.

Specifications

Variables	*Single Stocks*				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Panel A: W_p												
Disp Proxy	-99.95	-5.32	-130.85	-7.65	-174.07	-6.23	-171.39	-6.13	-161.96	-4.77	-175.04	-5.14
Adj.R^2	0.23		0.20		0.29		0.29		0.45		0.44	
Ob	145490		145490		14960		14960		7480		7480	
Panel B: W												
Disp Proxy	-32.72	-1.82	-72.80	-4.66	-196.85	-6.02	-195.49	-5.97	-151.27	-3.36	-159.01	-3.53
Adj.R^2	0.23		0.20		0.29		0.29		0.45		0.44	
Obs	145490		145490		14960		14960		7480		7480	
Panel C: W_{ps}												
Disp Proxy	-110.60	-6.58	-146.33	-10.05	-280.77	-8.28	-276.47	-8.15	-264.37	-5.40	-275.55	-5.64
Adj.R^2	0.23		0.20		0.29		0.29		0.45		0.44	
Obs	145490		145490		14960		14960		7480		7480	
Panel D: Aggregate 1												
	W_p				**W**				**W_{ps}**			
Disp Proxy	-93.35	-2.89	-126.30	-3.98	-108.43	-2.85	-132.91	-3.52	-153.30	-3.69	-195.55	-4.81
Adj.R^2	0.23		0.21		0.23		0.21		0.23		0.21	
Obs	145300		145300		145300		145300		145300		145300	
Panel E: Aggregate 2												
	W_p				**W**				**W_{ps}**			
Disp Proxy	-41.06	-0.56	-26.76	-0.36	-85.14	-0.97	-87.08	-0.99	-77.19	-0.82	-71.22	-0.75
Adj.R^2	0.69		0.69		0.69		0.69		0.69		0.69	
Obs	1496		1496		1496		1496		1496		1496	