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

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An important challenge to behavioral finance is to find a direct link between individual investor behavior and asset price dynamics. Few would doubt that large numbers of investors behave irrationally and are prone to behavioral heuristics that lead to suboptimal investment choices, although 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 biased investor marginality is a particularly difficult challenge because behavioral data are limited in scope and dimension. Beyond a few limited natural experiments such as in 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] finds a relation between aggregate fund flows and equity returns over long periods. Using individual fund flow data, Edelen and Warner [2001] show a high frequency correlation between flow data and the stock returns. In Goetzmann and Massa [2002, 2003] we establish causality from flows to prices and demonstrate that the shocks can be great. Goetzmann et al. [2000] find that behavioral factors (orthogonal to standard asset factors) cause dispersion of asset returns.

While all 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 in empirical testing is that most tests of behavioral effects are indirect. They rely on market price, return, and volume data, or upon market return anomalies (like overreaction or 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 the power to reject non-behavioral explanations.

Our approach is to seek a direct link between individual investor actions and asset price dynamics. We focus on the most widely documented behavioral heuristic among investors, the disposition effect. We connect our work to the theoretical literature on the implications of the disposition effect on stock prices (Grinblatt and Han [2005]) and test the relation between the preponderance of disposition investors trading an asset and the volatility, return, and trading volume of that asset.

We use a large sample of individual trading accounts over a six-year period, constructing a proxy for the prevalence of disposition investors in the market. We then show that on days a higher proportion of disposition-prone investors trade in a stock, its volatility, return, and trading

volume all decline. We show further that stock-specific disposition aggregates up to a common factor. Statistical exposure to this disposition-related factor explains cross-sectional differences in daily returns, after controlling for a host of other factors and characteristics.

Our results provide empirical evidence on the role of a behavioral bias in financial markets. We find that an abundance of disposition-prone investor trades dampen the price reaction to fundamental shocks. At the market level, this implies a generalized attenuation of market reactivity.

BACKGROUND

The *disposition effect* is the tendency to realize gains and defer losses. Also called loss aversion, it has generally been regarded as a direct implication of Kahneman and Tversky's [1979] prospect theory, which posits an asymmetry in attitude toward risk-taking, conditional upon a reference point. Shefrin and Statman [1985], for example, argue that because people dislike incurring losses much more than they enjoy making gains, and people are willing to gamble where losses are involved, investors will hold stocks that have lost value (compared to the reference point of their purchase price), and will be eager to sell stocks that have risen in value. Statman and Thorley [2006] point out that this bias, as it is based on a mental accounting framework, is stock-specific rather than related to the market as a whole.

Odean [1998] and Barber and Odean [2000] provide considerable empirical support for the extent of this disposition effect. Widespread evidence of loss aversion and the disposition effect has since been found and explored by other authors. Weber and Camerer [1998] use an experiment to document the effect for investors. Grinblatt and Keloharju [2000] find strong evidence of loss aversion in Finnish data.

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 suggests that the disposition effect may have a pricing impact.

Considerable theoretical analysis also suggests that behavioral biases, particularly loss aversion, could affect asset prices. For example, Shumway [1997] develops an equilibrium asset pricing model that assumes loss-averse investors, and shows that loss aversion induces investors to demand a higher risk premium for risk associated with negative market returns. Barberis and Huang [2001] and Barberis, Huang, Santos [2001] use prospect theory as the basis for examining pricing implications. They predict higher mean returns and volatility in an economy where prospect theory investors prevail.

Grinblatt and Han [2005] focus specifically on the disposition effect and develop a theoretical model to explain its equilibrium price implications. They relate the well-known momentum effect in stock returns to the amount of unrealized capital gains and losses in the stock, and to derive cross-sectional implications that they use to test their model.

MAIN TESTABLE RESTRICTIONS

We rely on the model developed by Grinblatt and Han [2005]. They derive closed forms for the stock price and trading volume as a function of fundamentals and disposition variables.

The idea is that the price of a stock is a function of both the fundamentals and the accumulated impact of prior capital gains and losses, weighted by a factor representing the impact of disposition investors. The return on a stock is a function of a backward-looking component and of the shocks to the fundamentals, deflated by the disposition effect. The stock price "under-reacts to public information about the fundamental value, holding the reference price constant" (Grinblatt and Han [2005]). That is, the disposition effect drives a wedge between the fundamental value of an asset and its market price.

The higher the proportion of disposition investors, the less sensitive the stock price is to current shocks to fundamentals. That is, the presence of disposition-prone investors reduces price fluctuations.

Grinblatt and Han [2005] 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. Note, however, that if the data were available, a more powerful test could be based on inspection of the representation of disposition investors in the market.

The intuition is that the stocks that are traded mostly by disposition investors will be less sensitive to fundamental shocks, and therefore will have a lower return and volatility. Therefore, conditional on a fundamental shock, all stocks will be affected but with an intensity

depending on the fraction of disposition investors in the market.

These considerations suggest that a direct test of the impact of disposition effect relies on estimation of the relation between 1) the fraction of disposition investors trading a specific stock and 2) the stock return and volatility. The null of a zero relation between the percentage of disposition investors trading a stock and returns and volatility is tested against the alternative of a negative relation.

The hypothesis is: *There is a negative relation between the fraction of disposition investors trading in a stock and its return and volatility level.*

This 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 reverse causality; when prices rise, investors who prefer to sell for a gain sell more. Such behavior is not surprising if investors are merely rebalancing toward an optimum.

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 losing stocks, there should be no direct relation between that definition and volatility. Theory would not suggest that disposition-prone investors are more willing to sell during periods of high volatility or buy during periods of low volatility. Finally, we can also consider the relation between the disposition effect and trading volume. In the case of the Grinblatt and Han model, the empirical results depend on the sample properties.

To test these restrictions, 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.

DATA

We use data provided by a nationwide discount brokerage house, used in the past by Odean [1998], Barber and Odean [2000], and Barber, Odean and Zhu [2003]. We call this hereafter the "individual investor database," or IID. The IID includes information on over 100,000 accounts for around 80,000 households. For each account, we have position files with end-of-month investor portfolios and daily transactions of all assets from January 1, 1991, through November 28, 1996.

For each transaction in an account, we know the security traded (identified in the case of a stock by the Center for Research in Security Prices 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 [2000] and look only at their equity holdings. We conduct our analysis at the investor level—i.e., concentrating on different accounts of the same investor—and consider each single buy and sell order for each account. There is no substantial reason to believe that the same investor behaves significantly differently in different accounts.

Exhibit 1 reports descriptive statistics in terms of average numbers of transactions per year. For each group, we report number of accounts, number of transactions, and the percentage (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 standardized by the length of time they are held. Turnover is calculated as the absolute sum of purchases and sales (expressed in terms of number of shares) divided by the average running balance.[1]

Panel B reports some disposition characteristics. That is, for each group, we separately consider buy-on-gain, sell-on-gain, buy-on-loss, and sell-on-loss transactions. For each category, we report the number of transactions and their percentage of overall transactions.

To draw inferences on the potential effects of the behavior of one class of investors on asset prices, we must have a representative sample. This is a general issue many authors address with respect to the database.

For example, Kumar [2002] compares his sample with a sample reported by the U.S. Census Bureau (Survey of Income and Program Participation [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 similar to the $16,900 account amount for the SCF 1992 and the $15,300 account amount for the SCF 1995. Barber and Odean [2000] report that the IID does not appear to be too geographically focused, or limited in terms of the distribution of income or trading characteristics.

EXHIBIT 1
Descriptive Statistics

Panel A. Groups of Accounts

		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
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. Disposition Characteristics

	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

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* U.S. retail investor in the market.[2]

CONSTRUCTION OF VARIABLES

As the dataset has already been used to assess the presence of a disposition bias (Odean [1998]), it allows us to skip the preliminary step of showing such a bias in the sample. Moreover, we can directly appeal to recent evidence that shows that such a bias induces investors to coordinate their trades (Barber, Odean, and Zhu [2003]). This suggests that the disposition bias, by inducing comovements in trade, could potentially have a market impact. We simply take 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 large 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 toward jointly disposition-prone and inframarginal investors, then the generality of our results might be questioned.

Although the brokerage sample may be tilted toward 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 toward price-setters in the capital markets. 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 Barber and Odean [2000] that our sample is representative at least in terms of including 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 or gain with respect to the current price, much 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 an investor bought or sold and therefore the moment at which the prior transactions were executed. Therefore, for our sample to be representative, we require that our investors, on average, trade in the same way as the population of U.S. investors does. If this is the case, and our investors are truly representative of the U.S. market, the factors we identify are representative of the behavior of the average investor.

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 stocks as a whole. Thus, we have no reason to expect 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.

Identifying Disposition Investors

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 use an example to describe the criterion we use to identify the disposition investors. Then we describe the two methodologies we use to construct our proxies of representation of the disposition investors in the stock.

For each transaction, we distinguish trades on-loss and trades on-gain. To identify sales-on-loss, we have to make some assumptions about the price at which the stock was purchased. We assume a last in first out or LIFO criterion for each individual investor; the last shares bought are assumed to be the first ones sold.[3]

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

In an example, consider this 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, 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 the transaction previously occurred, we record this as a sale-on-loss. If the difference is positive, we consider this a sale-on-gain.

For the data in Exhibit 2 we compute the gain or loss measures as follows. We start with the first buy operation on January 1, 1991. Calculation of the gain/loss for this transaction is indeterminate. Next, 200

EXHIBIT 2
Example Transaction

Transaction Date	Quantity	Price	Buy/Sell	Gain/Loss
910101	100	$100	Buy	–
910110	200	$70	Buy	200($70 − $100) = $−6,000
940101	210	$150	Sell	200($150 − $70) + 10 ($150 − $100) = $16,500
950103	50	$90	Sell	50($90 − $100) = −$500

shares are purchased on January 10, 1991. So the "buy-on-loss" is equal to: 200($70 – $100) = $ – 6,000. The next transaction is a sell. The investor is selling 210 at a price $150. Of these 210 units, the first 200 units are compared to the previous purchase price of 70, and the next 10 are compared to the purchase price of $100. So the total would be 200($150 – $70) + 10($150 – $100) = $16,500. This represents a sell-on-gain, realizing profit. Then, on January 3, 1995, the investor sells 50 shares at a price of $90. This represents a sell-on-loss equal to 50($90 – $100).

The LIFO criterion is an accounting convention adopted for the analysis. Its validity or relation to the disposition effect has not been tested experimentally, despite its intuitive appeal. While it is conceivable it could make our measure of the disposition effect less than perfect, it is not clear why the approach would bias our results one way or the other.

It is worth noting that we use the same convention for both buys and sells. That is, we identify whether each sale transaction represents a profit or a loss from the investor's standpoint. Analogously, we identify whether each purchase, using the previous transaction of the investor as anchor or reference point, took place at a loss—where the investor lost with respect to the previous transactions—or whether the investor gained.

Constructing Disposition Proxy

The intuition of the Grinblatt and Han [2005] model is simple: "The disposition effect creates a spread between a stock's fundamental value—the stock price that would exist in the absence of a disposition effect—and its market price." Stocks that are more demanded by disposition investors will be less sensitive to fundamental shocks and therefore will have a lower return and volatility. We therefore need to find a proxy for the representation of disposition investors in the stock demand, not an easy task.

One alternative is to determine the reference price indirectly by constructing a measure of unrealized capital gains (Frazzini [2006]). Another is to focus directly on the proportion of trades originated by disposition investors. If we find that, for a specific price, more rational investors sell than disposition investors (or that the net demand of the disposition investors is higher than the demand of rational investors), we can argue that at that price there is an imbalance among shareholders so that more disposition investors are willing to hold the stock than rational ones. This implies a higher fraction of disposition investors among shareholders, and thus lower return and volatility.

Therefore, we use as a first proxy the ratio of disposition-motivated sales over overall sales in the market. To identify the disposition-motivated sales, we use as a criterion the fact that disposition investors tend to hold losing stocks and sell winning ones. We thus define a variable W, constructed as the difference between the total dollar value of sells-on-loss and sells-on-gain, standardized by the sum of sells-at-loss and sells-at-gain:

$$W_t = \frac{(S_{lt} - S_{gt})}{(S_{lt} + S_{gt})} \tag{1}$$

where S_{lt} and S_{gt} are sell-on-loss and sell-on-gain transactions for day t. This variable increases as the value of sales-on-gain gets lower than the value of sales-on-loss; i.e., it increases as the percentage of sales by disposition investors (S_{gt}) shrinks with respect to sales by non-disposition investors (S_{lt}). In other words, this variable is greater for stocks with fewer disposition investors among sellers. That is, this variable increases as μ increases.[4]

The intuition is simple. If we observe that non-disposition investors sell more than disposition investors, then the fraction of disposition investors holding stocks increases. In other words, when W is high, there are fewer disposition investors among the investors *who are selling*. So, the stock is characterized by rational people who sell and disposition investors who hold onto the stock. Given that an increase in 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 losers—and therefore will be our main disposition proxy. Of course, it may be argued that we do not consider purchases. Therefore, even if the disposition effect in its strict formulation is defined just in terms of sales, for robustness we also construct variables that use the information in the buys.

Assuming that disposition investors sell the winning stock *and buy losing stocks* (i.e., buy-on-loss), we can construct other two proxies.[5] The first proxy (W_p) is the dollar value of total buys-on-loss minus buys-on-gain on a given day, standardized by the sum of buys-on-loss and buys-on-gain. The second alternative proxy (W_{ps}) combines the information from buys-on-loss and sells-on-loss. It is constructed as the difference between buy-on-loss plus

sell-on-loss and sell-on-gain minus buy-on-gain standardized by the sum of buy-on-loss, buy-on-gain, sell-on-loss and sell-on-gain.

These proxies are represented as:

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

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, buy-on-loss, buy-on-gain, sell-on-loss, and sell-on-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 far as five years in our sample.

This approach, while it has the advantage of being transaction-based and allowing for times variation in the degree of the disposition effect, is itself 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 spurious correlation with momentum strategies.

At the same time, note that whether the position is on-loss or on-gain is determined on the basis of each investor's reference price. This can date back as much as six years in our dataset. This implies that the same current price may result in a loss for one investor and a gain for another, depending on when the previous originating transaction (purchase in the case of current sale or sale in the case of current purchase) took place. Therefore, the potential for spurious correlation with current prices and with momentum strategies should be very low.

Alternative Way to Construct Disposition Proxy

To address the spurious correlation issue more directly, we identify disposition investors on an out-of-sample basis. That is, we first define as disposition-prone the investors who, in a month, have *sold winners and held onto losers,* and then we track their behavior in the month following. This procedure allows us to define the investors in-sample and to construct the behavioral factors out-of-sample, avoiding a selection bias.

To implement this approach, we follow the methodology developed by Odean [1998]. For each investor, we focus on *realized* gains and losses and *paper* gains and losses. Each day, we identify for each investor the *realized* gains or losses. These are constructed by comparing the selling price for each stock and its purchase price.

For all other stocks in the portfolio that are not sold, we also construct daily *paper* gains or losses by comparing the purchase price of each stock (the price at which it is held in the portfolio) to the stock's high and low price for that day. According to Odean [1998]:

> 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 [the] 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 and losses as well as the daily *realized* gains and losses, and construct for each investor the ratios:

$$PGR = \textit{Proportion of Gains Realized} = \frac{\textit{Realized Gains}}{\textit{Realized Gains} + \textit{Paper Gains}}$$

$$PLR = \textit{Proportion of Losses Realized} = \frac{\textit{Realized Losses}}{\textit{Realized Losses} + \textit{Paper Losses}}$$

We use these ratios to identify the disposition investors. 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 and gains.

We classify gains and losses this way each month. Then, we trace the behavior of the different classes of investors in the next month. That is, *the next month*, each day, we separately identify the net trades (i.e., net demand) of the different classes of investors, and we use them to construct our disposition proxy. This variable—constructed as the difference between the net trades of disposition investors and the net 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.

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 because more trades occur for them, which increase 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 large stocks, the number of trades would be too low to construct proper proxies of disposition trades and to run a meaningful analysis. Moreover, the very fact that large stocks are heavily traded by institutional investors, biases the test against us, making it harder to find a relation.[6]

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. Anshuman et al. [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 et al. [2002] have shown 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:

$$\sigma_t = \log[\max_{\{s \in Day_t\}} P_{s,t} - \min_{\{s \in Day_t\}} P_{s,t}] \qquad (2)$$

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 *t-th* day). We omit the subscript *i* to denote the *i-th* stock for simplicity.

The analysis uses 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 (the T-bill rate); the return on the stock; the volatility of the stock and the logarithm of its volume. These account for marketwide variations (the former) and stock-specific characteristics (the latter), changing with daily frequency. The Fama and French factors, as per Fama and French (1992, 1993) as well as the riskless rate, come from Kenneth French's web page. The returns on the stocks are derived from the daily CRSP files.

IMPACT OF DISPOSITION EFFECT AT STOCK LEVEL

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 relation at the aggregate level. That is, we study whether the impact of the disposition effect aggregates at the overall market level.

Disposition Effect and Stock Return, Volatility, Turnover, and Trading Volume

We begin to examine 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 estimated is:

$$Z_{it} = \alpha + \beta W_{it} + \gamma C_{it} + \varepsilon_{it} \qquad (3)$$

where Z_{it} is the dependent variable that, in the different specifications, is alternatively stock return, return volatility, turnover, and trading volume; W_{it} is the disposition proxy; and C_{it} is a vector of control variables. The broadest set of control variables includes: the daily values of the Fama and French factors (*market*, *HML*, *SMB*), the riskless rate, company size, overall market volume, stock price, and volume. Recall that we would expect $\beta < 0$ in the case of return and volatility. As a robustness check, we report two alternative specifications that differ for whether the stock price is included (Specification I) or not (Specification II) among the control variables.

We consider alternative minimum units of analysis, by grouping stocks in size-based 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 in the portfolio.

The disposition variable is the average ratio calculated for those specific stocks in the portfolio. Grouping stocks in portfolios lets us average stock-specific idiosyncratic shocks to see whether the difference between portfolios is related to our variable of interest.

The results reported in Exhibit 3 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 inclusion of the control variables and to the change of 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 both statistically and economically significant. An increase of one standard deviation in our disposition proxy—i.e., the standardized difference between disposition investors and other investors—reduces stock return by 7 basis points a day, or 1.56 times the average daily return. As we have noted, given that investors are defined as disposition-prone on the basis of their willingness to hold onto losing stocks, there should not be any direct relation between their definition and volatility. Therefore, the robust negative relation between volatility and our disposition proxy provides important evidence in favor of our working hypothesis, suggesting that our results on returns are not a result of reverse causality.

EXHIBIT 3
Disposition Proxy and Stocks

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

Disposition proxy (W) is constructed as the ratio between sell-on-loss minus sell-on-gain standardized by the sum of sell-on-loss and sell-on-gain (divided by 1,000). Control variables include daily values of Fama and French factors (market, HML, SMB), riskless rate, company size, logarithm of the average market volume and stock price, overall market volatility, and company and time-specific constants. To estimate Equation (3), we adopt a pooled estimation with a robust variance-covariance matrix, overall market volatility, and time and company dummies. Specification I includes. Specification II does not.

Finally, it is important to note that the disposition proxy effectively explains 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 counterparties affects relative prices.

Additional Robustness Checks

Are these effects just the result of a spurious correlation, due to the way we identify our disposition proxies? This is an important question.

To address it we identify disposition investors in an alternative way: out-of-sample, based on trades of investors in the previous month. This allows us to control for the possibility of spurious correlation that may arise because of short-term momentum or mean reversion. There is no reason why this criterion of identification would be spuriously related to current market prices.

The results for alternative approaches reported in Exhibit 4 again 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 stocks into portfolios. These findings show that our results are robust to the way we identify disposition investors. This suggests that, at the stock level, the disposition effect does indeed affect stock prices, as predicted by theory.

Alternative Definitions of Disposition Effect

We also use two alternative disposition proxies based on purchases (W_p) and on net purchases (W_{ps}), and again consider the impact on volatility, return, turnover, and trading volume.

The results are reported in Exhibit 5. Panel A reports the results for the proxy based on purchases, and Panel B the results for the proxy based on net purchases. Once again the results show a negative and statistically significant correlation between the disposition proxy and stock return, volatility, turnover, and trading volume, and these findings are robust across alternative specifications and for different groupings of stocks into portfolios.

EXHIBIT 4

Alternative Ways of Identifying Disposition Investors I—Out-of-Sample

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

EXHIBIT 5

Alternative Ways of Identifying Disposition Investors II—W_p and W_{ps}

Panel A. W_p

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

The robust negative relation between volatility and this disposition proxy provides added evidence in favor of our working hypothesis, that investors are defined as disposition-prone on the basis of their willingness to hold onto losing stocks in the previous month. It is unlikely that spurious correlation or reverse causality would induce investors to behave in such a way that their representation in the market is negatively related to volatility. This supports Grinblatt and Han's [2005] theory, and shows that our evidence is robust to the way we identify the disposition investors.

Alternative Econometric Methodology

In one final check, we adopt a different econometric approach to estimate Equation (3), following the Fama-MacBeth methodology. We run a series of daily cross-sections (at the individual stock level or based on ten or five portfolios) on our disposition proxy and the stock-specific control variables. Then, we calculate the mean and statistical significance of the estimated coefficients across the cross-sections. This methodology does not exploit the time series dimension, but is more robust to spurious correlation due to trends or non-stationarity.[7]

We consider both our main disposition proxy (W) and the alternative ones (W_p and W_{ps}) along with alternative specifications. That includes two alternative specifications that differ for whether the stock price has been included (Specification I) or not (Specification II) among the control variables. We also consider alternative groupings of the stocks in portfolios.

The results are displayed in Exhibit 6. Panels A report the results for the proxy based on purchases, Panels B the results for the proxy based on sales, and Panels C the results for the proxy based on net purchases. We show both the value of the coefficient of interest (β) as well as the average adjusted R^2 of the second stage of the procedure.

We again 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.

EXHIBIT 5 (*continued*)

Panel B. W_{ps}

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

Alternative disposition proxies: W_p is constructed as the ratio between buy-on-loss minus buy-on-gain standardized by the sum of buy-on-loss and buy-on-gain. W_{ps} is constructed as the ratio between buy-on-loss plus sell-on-loss minus sell-on-gain minus buy-on-gain standardized by the sum of buy-on-loss, buy-on-gain, sell-on-loss, and sell-on-gain. Both W_p and W_{ps} are divided by 1,000.

IS THE DISPOSITION EFFECT STOCK-SPECIFIC?

So far we have shown that the disposition effect influences stock volatility, return, and trading volume by dampening stocks' sensitivity to shocks to the fundamentals. And indeed, shocks to the fundamentals are the only source of uncertainty in Grinblatt and Han's [2005] model.

The next step is to see whether the disposition effect is a stock-specific characteristic or whether it is aggregate at the market level. That is, some exogenous event (e.g., a liquidity shock) may also change the representation of disposition investors in the market.

A change in the representation of disposition investors in the overall market has a direct impact on returns and volatility. Let us see why this may be the case. We know that disposition investors tend to hold losers and sell winners. This implies that, if stocks are doing well and prices are above their reference points, an increase in the percentage of disposition investors (i.e., the holders of losing stocks and sellers of winning stocks) reduces net demand, thus lowering prices, returns, and volatility. If this effect aggregates at the market level, changes in the representation of disposition investors may behave as a common factor.

Stocks with a positive loading on the presence of disposition investors—i.e., stocks whose disposition-motivated trades increase with the increase of disposition-motivated trades in the market—should have a lower realized return and trade at a discount. Conversely, stocks with a negative loading on it—i.e., stocks whose disposition-motivated trades decline with an increase of disposition-motivated trades at the market level—should have a higher realized return and trade at a premium. In other words, stocks for which there are fewer disposition investors should command a higher return, while stocks for which there are more disposition investors should have a lower return.

EXHIBIT 6
Alternative Econometric Specification

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

This reasoning follows Pastor and Stambaugh [2003], who point out that order flow represents a source of uncertainty on its own. In our case, 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 would represent a non-diversifiable source of uncertainty. Marketwide shocks to the disposition factor—proxied by 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 the aggregate disposition effect. The source of these shocks—the results of the aggregation of stock-specific transaction-related shocks—is caused by fluctuations in the level of the active disposition investors. An increase in 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.

Aggregate Disposition Effect and Market Variables

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 100 stocks the trades of the different classes of 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-level approach. First, we perform the analysis at the individual stock level, and then 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

EXHIBIT 6 (*continued*)

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
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	

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, the econometric methodology, and the set of explanatory and control variables are the same as in our base case. In the case of the second specification, the stock-specific control variables are aggregated by averaging them out for all the stocks in the portfolio. The results are displayed in Exhibit 7. Panel A reports the results for the specification estimated at the individual stock level, and Panel B reports the results for the specification estimated at the aggregated level. For brevity in the text, we focus on the main disposition proxy (*W*).

The results in Exhibit 7 are similar to the results for 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 different specifications and different ways of constructing the disposition proxy. Moreover, the results carry through at the market level, except that they are less significant for trading volume. Thus not only does disposition matter at the *individual* security level, but the aggregate behavior of disposition investors also appears to matter at the *aggregate* level, suggesting that behavior effects might be important marketwide.

These results hint at the possibility that the disposition effect has a marketwide impact. Note in particular that stock returns are affected by a marketwide disposition effect. An increase in the aggregate disposition variable reduces stock returns by 12 basis points a day or 1.3 times the average daily return.

EXHIBIT 7
Disposition Index and Market Variables

Panel A. Individual Stocks and Common Factors

	Factor W_p				*Factor W*				*Factor W_{ps}*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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. Market and Common Factors

	Factor W_p				*Factor W*				*Factor W_{ps}*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	

The relation between returns and the disposition effect we uncovered at the individual stock level earlier is consistent with the idea that the disposition proxy is a characteristic of individual stocks, whether due to fundamentals or style preferences. The results for the aggregate market are, by contrast, consistent with a conclusion that the disposition effect is an aggregated risk factor on which all stocks load. The latter seems a priced factor.

These explanations of course are not mutually exclusive. Indeed, 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 shocks (innovations) to the fundamentals, while the former relates only to past shocks.

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

Is There a Common Disposition Factor?

Just six years of data do not allow us to draw definite conclusions about pricing, but we can assess whether stock returns *co-move with a marketwide 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-sectional test, applied to daily returns.

In preliminary evidence, we compute the differential return due to the disposition effect and assess its statistical significance. We follow standard techniques and estimate 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 (CAPM), the market factor is the return on the market, and in the second (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 with a similar level of disposition proxy.

We consider three alternative return portfolios: the top (bottom) 10%, 20%, and 30%. For example, the top (bottom) 10% portfolio includes all the stocks in 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 equally weighted and value-weighted averages.

The results reported in Exhibit 8 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 the top and bottom 20%, and differences between the top and bottom 30%. It is also robust to the way we construct our disposition proxy. The results are both statistically and economically significant. The disposition effect seems to affect returns by an average of 10 basis points (with a minimum impact of 10 bp and a maximum impact of 50 bp).

We then test for the presence of a common disposition factor. We follow two approaches, first we use individual stock returns, and then size-sorted portfolios. To construct the disposition factors, once we identify the daily trades and the different classes of investors and construct our disposition proxy, we build portfolios based on them, following the Fama and French [1992] procedure. That is, we rank stocks on the basis of the disposition proxy, and then construct return-based factors defined as 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. Twenty-day rolling windows generate 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 β, estimated via a time series regression. Then, the β, are used in a second-pass regression along the lines of Fama and MacBeth.

At this stage we also include characteristics such as 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

EXHIBIT 8
Abnormal Returns of Disposition Portfolios

	Top 10%–Bottom 10%				Top 20%–Bottom 20%				Top 30%–Bottom 30%			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Equally Weighted												
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 Weighted												
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

Alphas constructed by regressing the difference between the returns of high-disposition portfolios and low-disposition portfolios on a constant and risk factors. There are two alternative specifications: in the CAPM the market factor is the return on the market. In three-factors, the factors are the three Fama and French factors (market, HML, and SMB).

different number of factors and characteristics. We also consider cases with different disposition factors. 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 three days of leads and lags, and in the second five days of leads and lags.

Our disposition factor acts as a proxy for the aggregate level of the disposition effect. It increases as the representation of disposition investors in the market rises. We expect a negative value of the coefficient on the disposition loading—i.e., the disposition factor should be a discount.

The results in Exhibits 9 and 10 provide some evidence in favor of a common disposition factor, at least over this limited six-year time interval. The regressions in Exhibit 9 are estimated at the individual security level, while the regressions in Exhibit 10 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, consistent with findings so far. These results hold across all the specifications, regardless of the number of additional factors (one- or three-factor model) and characteristics (volume, volatility, turnover) that we include.

This suggests not only that the disposition bias of investors appears to affect the returns of the companies in which they trade, but also that the exposure of a stock to

EXHIBIT 9

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

Panel A. Three Days of Leads and Lags

	I		*II*		*III*		*IV*		*V*		*VI*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Disposition Factor F_{Wp}												
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												
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}												
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	-	-	-	-	-	-	-	-	-	-

the aggregate percentage of disposition investors in the market is associated with lower ex post returns. These findings support the hypothesis that a higher fraction of disposition investors in the market reduces price pressure and lowers ex post returns.

A Liquidity-Based Explanation?

What is the economic intuition behind these findings? One explanation might have to do with liquidity. That is, the disposition effect, by reducing the stock reaction to fundamental shocks (ε_{Ft}), should also enhance 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 proxies for liquidity, this would suggest that the disposition effect reduces liquidity.

To address this issue, we consider a measure of liquidity based on the illiquidity ratio of Amihud [2002]. The illiquidity ratio at day t is defined as:

$$ILLIQ_t = \frac{|Ret_t|}{V_t P_t}$$

where Ret_t is the stock return on day t, and $V_t P_t$ is dollar volume in millions of dollars. This variable represents

EXHIBIT 9 (*continued*)

Panel B. Five Days of Leads and Lags

	I		*II*		*III*		*IV*		*V*		*VI*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Disposition Factor F_{Wp}												
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	-057	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												
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}												
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	-	-	-	-	-	-	-	-	-	-

Factors are defined as F_{Wp}, F_W, and F_{Wps} (for the disposition proxies W_p, W, and W_{ps}). Also included are some characteristics such as the volatility of 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.

the percentage price response to a certain trading volume.

Amihud [2002] shows the percentage price response 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], who shows that the daily value of this measure is strongly correlated with a high-frequency estimate of liquidity, considers it the "the most reliable proxy relationship." Acharya and Perdersen [2005] use this measure at monthly frequency, by aggregating its daily values. The inverse of $ILLIQ_t$ is our measure of liquidity.

According to the illiquidity equation, an increase in the proportion of disposition investors (μ) affects liquidity depending on the level of μ itself. For low values, an increase in μ increases liquidity. For higher levels, an increase in μ reduces liquidity.

The intuition is simple. As the proportion of disposition investors in the market rises, stocks become less sensitive to shocks. For low levels in μ, an increase in μ raises trading volume and reduces returns. The two effects reinforce one another to increase liquidity (i.e., the numerator of $ILLIQ_t$ declines and the denominator increases). For higher values in μ, however, an increase in μ reduces trading volume. This effect more than offsets the drop in return, reducing liquidity.

Is this reflected in the data? We analyze whether the disposition effect affects liquidity, both at the individual

EXHIBIT 10

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

Panel A. Three Days of Leads and Lags

	I		*II*		*III*		*IV*		*V*		*VI*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Disposition Factor F_{Wp}												
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												
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	-	-	-	-	-	-	-	-	-	-
Disposition Factor F_{Wps}												
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	-	-	-	-	-	-	-	-	-	-

stock level and at the aggregate market level by regressing liquidity on the disposition proxy and control variables. We first for each stock regress its liquidity on the disposition proxy defined at the stock level and control variables.

The findings are reported in Exhibit 11 Panels A, B, and C, for alternative disposition proxies (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 inclusion of control variables (Specifications I and II) and to a change in the disposition proxy.

Panels A and B report results for disposition proxies aggregated across all stocks. In Aggregate 1, we regress stock liquidity on the aggregate value of our disposition proxies and control variables. In 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 findings in Panel D confirm the other findings, but at the market level (Panel E), 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, contrary to what the theory predicts, the data suggest that lower stock returns should be related to a reduction in liquidity.

EXHIBIT 10 (*continued*)

Panel B. Five Days of Leads and Lags

	I		*II*		*III*		*IV*		*V*		*VI*	
Variable	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Disposition Factor F_{Wp}												
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	-	-	-	-	-	-	-	-	-	-
Disposition Factor F_W												
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	-	-	-	-	-	-	-	-	-	-
Disposition Factor F_{Wps}												
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	-	-	-	-	-	-	-	-	-	-

CONCLUSION

Measuring the impact of behavioral biases on asset prices is difficult, because econometricians rarely have access to individual investor decisions. For analysis of the widely documented disposition effect, we construct a variable based on investor trades that serves as a proxy for the representation of disposition-prone investors in the market and test how it relates to stock return, volatility, and trading volume.

The results indicate a strong negative correlation between the disposition effect and stock return, volatility, and trading volume. We also show that the disposition effect is not just stock-specific, but that it aggregates at the market level, forming a factor that affects returns, volatility, and trading volume. This generates a common price-relevant factor that disperses stock returns. The exposure of a stock to this disposition factor is associated with lower ex post returns.

ENDNOTES

[1]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: $H_i = \Sigma_{t=b}^{s} N_{i,t}(s-b)$. We then divide this by the number of days the account is open in the period to calculate the running balance, the difference between the first and last holding dates for investor i $RB_i = H_i/[\max(t_i) - \min(t_i)]$.

[2]Some transactions are executed on the Internet (for details, see Barber and Odean [2000]).

[3]That is, for each single investor we aggregate the different accounts. Every sell until the first buy operation within the period 1991–1996 is ignored.

EXHIBIT 11
Liquidity and Disposition Proxy

	Single Stocks				*10 Portfolios*				*5 Portfolios*			
	I		*II*		*I*		*II*		*I*		*II*	
Variable	*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	
Obs	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	

Liquidity of each stock regressed on the disposition proxy defined at the stock level and control variables. Aggregate 1 regresses stock liquidity on the aggregate value of disposition proxies and control variables. Aggregate 2 regresses the aggregate (average) value of liquidity on the aggregate value of disposition proxies and the aggregate (average) value of the control variables. Coefficients are divided by million.

[4]Indeed, the fewer disposition investors are among sellers, the higher should be the representation of disposition investors among the net demand of the stock.

[5]We can think of the disposition investors as holding onto losing stocks. So, if they rebalance their portfolios dynamically over time, they appear to be buying losing stocks (with respect to their reference point) more often than the non-disposition investors. This would show up as a positive difference between their buys-on-loss and the buy-on-loss of the non-disposition investors. So, on average, we expect that the amount of buys-on-loss proxies for purchases by disposition investors. The buys-on-gains should, instead, proxy for purchases by non-disposition investors. Indeed, if disposition investors sell the winning stocks (with respect to their reference point) they should not simultaneously buy them back.

[6]Institutions take the other side of the trade, exploiting retail investors' behavior. Therefore, retail investors' trade should directly impact institutions' trades and thus prices.

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

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