Internet Appendix to "Do Limit Orders Alter Inferences about Investor Performance and Behavior?"*

This Internet Appendix contains details on three additional analyses that were omitted from the body of the paper for brevity. The first part examines why individual investors use limit orders. In particular, the first section discusses the theory of order choice, measures the relation between individuals' order choices and the state of the market, and compares individuals' order choices to choices made by different types of traders in the limit order book model of Goettler, Parlour, and Rajan (2009). The second part replicates the main tests of Gutierrez and Kelley (2008) on the long-lasting momentum in weekly returns using Finnish return data. In the body of the paper I note that the similarity between this momentum pattern and the limit order loss pattern suggests that price momentum may be the primary driver of limit order losses. Finally, the third part uses U.S. brokerage firm data to study the sensitivity of disposition effect estimates to same-day stock price movements. Because price movements drive limit order executions, this analysis provides indirect evidence on the economic significance of the limit order effect in the U.S. data set.

I. Why Do Individuals Use Limit Orders?

A. The Theory of Order Choice

A trader's order choice results from the optimal weighing of the costs and benefits associated with market orders and limit orders. Market orders' key benefit over limit orders is their execution certainty. A limit order fails to execute when the market price moves away from the limit order. If a limit order fails to execute, the trader has to complete the trade at an unfavorable price. Limit orders' benefit over market orders is that, conditional on execution, a limit order gives a more favorable execution price than a market order.

Adverse selection risk is a distinct cost borne by limit orders. Limit buys execute more often when the market price drops and limit sells execute more often when the market price increases. Copeland and Galai (1983) frame this problem by modeling limit order submissions (or, in their application, the setting of market maker quotes) as writing options. If an informed trader hits the limit order, the option is exercised in the money.

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A trader weighs these costs and benefits to choose optimally between market orders and limit orders, and, if the trader chooses to place a limit order, to specify the limit price. If a trader's objective is to minimize the expected purchase price or to maximize the expected sale price, then a trader submits a limit order when the benefit of earning the bid-ask spread offsets adverse selection and non-execution risks.[1] If traders can monitor the market and revise their orders, then they may initially place limit orders far away from the market price and then gradually change limit prices to increase order aggressiveness. At the end of the trading window, if necessary, traders switch from limit orders to market orders.[2]

Traders' objectives and information sets affect order choices because they influence the costs and benefits of market and limit orders. For example, an investor who is forced to sell immediately must submit a market order regardless of market conditions. The effect of information is more ambiguous. Many studies assume that informed traders rely exclusively on market orders while uninformed traders use both limit and market orders.[3] By contrast, Bloomfield, O'Hara, and Saar (2005) analyze experimental asset markets and find that informed traders use limit orders to provide liquidity. Chakravarty and Holden (1995) and Kaniel and Liu (2006) find that informed traders' optimal strategy is a mix of limit and market orders.

In a limit order market, each trader's order choice also depends on the choices of all other traders. A limit order will not execute if no one is willing to submit a market order, and a market order can only be submitted when there are unexecuted limit orders in the limit order book. Hasbrouck and Saar (2002) call the consequences of any such interdependencies "the equilibrium effects." These effects can either amplify or counteract initial changes. Suppose, for example, that the arrival rate of market orders increases. This change increases the attractiveness of limit orders because the likelihood of execution increases. But because market orders are submitted by traders who choose them in preference to limit orders, the increased attractiveness of limit orders necessarily decreases the use of market orders. This decrease in turn lowers the likelihood of execution and offsets the initial shift in the use of limit orders.[4]

The interdependencies between traders' order choices call for the use of equilibrium models of the limit order book. Studies such as those by Parlour (1998), Foucault (1999), Foucault, Kadan, and Kandel (2005), Goettler, Parlour, and Rajan (2005, 2009), and Roşu (2009) examine dynamic equilibrium limit order book models in which investors choose optimally between limit orders and market orders. Each trader in these models conditions on the actions of all other traders, and all liquidity arises endogenously from traders' optimal choices. These models permit analytical solutions only under very restrictive assumptions. For example, Parlour (1998) assumes a constant value for the fundamental value of the asset and allows for a limit order book that has only two price levels, the bid and the ask. Foucault's (1999) model requires that limit orders remain in the book only for one period. Other models, such as the models in Goettler, Parlour, and Rajan (2005, 2009), relax these assumptions but pay the cost of losing analytical tractability.

[1]See, for example, Handa and Schwartz (1996) and Foucault (1999).

[2]See, for example, Harris (1998) and Hasbrouck (2007).

[3]See, for example, Glosten (1994). Bloomfield, O'Hara, and Saar (2005) discuss the prevalence of this assumption.

[4]See, for example, Cohen et al. (1981) and Hasbrouck and Saar (2002).

B. Empirical Analysis of Investors' Order Choices

The abundance of unobservable factors hinders the analysis of traders' order choices. However, some of the comparative statics in the theoretical order choice literature are similar across studies and yield testable predictions about investors' order choices. First, if the bid-ask spread widens but other market conditions remain unchanged, then limit orders become more attractive relative to market orders. Second, if the arrival rate of the market orders on the opposite side of the market increases, then limit orders become more attractive as the likelihood of execution increases. Similarly, an increase in the arrival of rate of market orders on the same side of the market decreases the attractiveness of limit orders. The reason is that such an increase makes limit orders more attractive for traders on the other side of the market, which in turn decreases the likelihood of execution on the same side of the market.

Table IA.I examines how variation in the size of the bid-ask spread and in market order arrival rates influences individuals' and institutions' order choices. To identify variation in these quantities while keeping other market conditions fixed, I measure within-day and within-stock changes in bid-ask spreads and market order arrival rates. I assume that during one trading day in one stock, most of the variation in the bid-ask spread and market order arrival rates arises for reasons unrelated to changes in fundamental market conditions.

I record the state of the market an instant before each new order is submitted. I measure the arrival rates of the same- and opposite-side market orders for a five-minute period leading up to each new order. At the end of each trading day for each stock, I rank bid-ask spread observations into quintiles. I also rank same- and opposite-side non zero market order arrival rates in three equal-sized categories. I assign zero arrivals to a separate category. Because the limit order data contain only approximate investor identities for unexecuted limit orders, I study brokers who cater (almost) exclusively either to individuals or institutions. Over three-quarters of trades of brokers EQ and LEP originate from households, suggesting that these brokers' microstructure behavior largely represents individuals' order choices. At the other end of the spectrum, individual investors account for less than 2% of the trades executed by brokers ALF, AG, ES, NET, SG, UBS, DB, and SWB. All other brokers fall between these two extremes. I use these two broker groups to separate individual investors from institutional investors. Investors submit 2.0 million and 1.9 million orders through these two broker groups, respectively, and jointly account for 36% of all incoming orders.

Panel A of Table IA.I reports on individual and institutional investors' limit order submission rates as a function of the size of the bid-ask spread. Although individual investors tend to use more limit orders regardless of the size of the spread, both groups increase their use of limit orders as the spread widens. Individuals' use of limit orders increases monotonically by 21.7 percentage points as the spread widens from the lowest to the highest quintile. Institutions increase their use of limit orders by 30.4 percentage points.

Panels B and C report on investors' limit-order submission rates as a function of market order arrival rates on the same (opposite) side of the market. Both investor groups submit more limit orders when the arrival rate of counterparty market orders is high and the arrival rate of same-side market orders is low (the top right-hand corner of each panel). Investors are less likely to submit market orders when these market order arrival rates flip around. Individual investors' limit order use increases monotonically by 22.6 percentage points from corner to corner, and institutional investors' use increases by 32.5 percentage points. Thus,

Table IA.I
Investors' Limit Order Use Conditional on the Bid-Ask Spread and Recent Market Order Arrival Rates

This table reports on the fraction of limit orders in individual investors' and institutional investors' order flow as functions of the bid-ask spread and the recent market order arrival rates on the same side and on the opposite side of the market. I assign all state variables, which I measure an instant before each order is submitted, into bins separately for each day and each stock. I rank bid-ask spread observations into quintiles and same- and opposite-side non zero market order arrival rates in three equal-sized categories. I assign zero arrivals to a separate category. "Individual investors" are the two most household-intensive brokers in the data. "Institutional investors" are the eight most institution-intensive brokers in the data. Panel A reports on the fraction of limit orders in the order flow as a function of the bid-ask spread quintile. Panels B and C report on the fraction of limit orders in the order flow as a function of the market order arrival rates. In all computations I use data from the Helsinki Stock Exchange from September 18, 1998 through October 23, 2001.

Panel A: Investors' Limit Order Use (%), Bid-Ask Spread

	Individual Investors		Institutional Investors	
Bid-Ask Spread Quintile	Limit Orders	N	Limit Orders	N
Low	60.41	263,143	39.63	193,094
2	67.57	220,315	46.65	179,771
3	72.84	216,975	51.98	177,233
4	77.75	220,113	58.19	177,197
High	82.82	221,864	68.69	171,562

Panel B: Individuals' Limit Order Use (%), Market Order Arrival Rates

		Five-Minute Arrival Rate of Opposite-Side Market Orders			
		None	Low	Medium	High
	None	78.08	78.37	80.68	83.53
Five-Minute Arrival Rate of Same-Side Market Orders	Low	63.21	72.04	74.50	76.22
	Medium	60.05	67.08	70.33	71.96
	High	58.34	63.52	64.97	65.70

Panel C: Institutions' Limit Order Use (%), Market Order Arrival Rates

		Five-Minute Arrival Rate of Opposite-Side Market Orders			
		None	Low	Medium	High
	None	62.32	67.13	72.50	76.87
Five-Minute Arrival Rate of Same-Side Market Orders	Low	48.50	51.01	54.58	59.11
	Medium	44.26	46.12	49.70	53.81
	High	44.46	43.56	44.88	49.50

both types of investors respond to changes in market conditions similarly, and in a way that is consistent with the predictions of the order choice literature.

C. Comparing Investors' Order Choices to Model-Based Simulations

I further examine the order choices of both individual and institutional investors by comparing these investors' behavior to numerical solutions of the state-of-the-art dynamic limit order book model of Goettler, Parlour, and Rajan (2009). This model adds several realistic features over earlier models. First, traders optimally choose whether to acquire information about the asset and the type of order to submit, and traders can also refrain from trading. Second, asset prices are discrete and limit orders execute according to time and price priority. Third, traders' initial arrivals follow Poisson processes and traders can revisit the market an arbitrarily large number of times. Fourth, traders can endogenously choose to cancel or modify their orders as they revisit the market. Fifth, the asset's fundamental value follows a stochastic process. Sixth, uninformed traders learn about the asset's fundamental value from all market observables, including the limit order book and the most recent transaction.

The financial asset in this model has both common and private components to its value. The private component of value generates an intrinsic motive for trade. Traders with low private values are traders who need to sell because of a negative liquidity shock. Also, because some traders want to trade for private reasons, other traders with no private value component (and no information) have an incentive to provide liquidity.

I use the high-volatility regime parametrization in Goettler, Parlour, and Rajan (2009) with two generalizations. First, I split the trader population in two and give one-half of the population a discount rate of 0.03 and the other half a discount rate of 0.09. Because the discount rate determines the cost of delaying a trade, this modification creates two types of traders: patient traders and impatient traders. (Goettler, Parlour, and Rajan (2009) give each trader the same discount rate of 0.05.) Then, instead of studying an equilibrium in which either only those traders with no private value components are informed or all traders are informed, I examine a market in which half of the traders acquire information and the others do not. (Goettler, Parlour, and Rajan (2009) show how to back out a distribution of information acquisition costs that sustains equilibrium with any conjectured information structure.) I draw private value component realizations and information acquisition choices independently of each other.

While Goettler, Parlour, and Rajan (2009) examine the wedge that asymmetric information drives between the observed and fundamental price processes, I use their model to study traders' order choices. I solve the model numerically for stationary symmetric equilibrium in which each type of trader chooses the same strategy in the same state of the game. After solving numerically for the equilibrium, I simulate 2.1 million entries (or reentries) from the model. I discard the first 0.1 million observations to burn in the market. I examine traders' order choices in these simulated data, splitting the sample by whether the trader is informed or uninformed, by whether the trader is patient or impatient, and by the realization of the private value component. Then I compare the determinants of order choices in these simulations to the determinants of order choices in actual data.

I summarize the state of the market at the time of each arrival by using the following eight variables: the natural logarithm of the bid-ask spread; the squared bid-ask spread;

the change in the bid-ask spread from five minutes ago; the signed change in the midpoint of the bid-ask spread from five minutes ago, that is, $\ln(\mathrm{mp}_t/\mathrm{mp}_{t-5\mathrm{min}})$ for buy orders and $-\ln(\mathrm{mp}_t/\mathrm{mp}_{t-5\mathrm{min}})$ for sell orders; the natural logarithm of the number of market order arrivals on the same (opposite) side of the market during the preceding five-minute period (plus one); and the natural logarithm of the number of limit order arrivals on the same (opposite) side of the market during the preceding five-minute period. I assume that one unit of clock time in the model corresponds to one minute of trading.

In Table IA.II, Panel A reports on a set of logit regressions, which I estimate using the simulated data. In these regressions, I set the dependent variable to one if the trader submits a limit order and to zero if the trader submits a market order. Each regression also reports the average proportion of limit orders submitted by each trader type. The results reveal that each trader type employs a mix of limit orders and market orders, consistent with the predictions in Chakravarty and Holden (1995), Bloomfield, O'Hara, and Saar (2005), and Kaniel and Liu (2006). Traders' order choices are also strongly state-dependent. Traders are more likely to submit limit orders when the bid-ask spread is wide or has just widened, when the midpoint of the bid-ask spread has moved away from the trader, and when the flow of market orders on the opposite side of the market has been high. The second-order effect of the bid-ask spread is negative, indicating that the likelihood of a trader choosing a limit order over a market order increases at a decreasing rate as the spread widens. Recent limit order arrival rates also influence order choices, but the signs vary across trader types and private value component realizations.

The estimates in Table IA.II indicate that information, patience, and private value component realizations affect not only unconditional limit order usage rates, but also each trader's sensitivity to the state variables. For example, as seen in the all-private-values column, informed traders are more sensitive than uninformed traders to changes in market conditions and also use more market orders. Impatient traders and traders with extreme private value component realizations submit more market orders. Traders' sensitivity to market conditions, particularly to those related to the bid-ask spread, increases significantly in the magnitude of the private value component. For example, the bid-ask spread slope coefficient more than doubles for three of the trader types when moving from traders with no intrinsic motive to trade (Private $v = 0$) to traders with the largest private value component realizations ($|\text{Private } v| = 8$).

In Table IA.II, Panel B reports on analogous logit regressions that I estimate by using actual microstructure data. I estimate the regressions separately for individual investors (brokers EQ and LEP) and institutional investors (brokers ALF, AG, ES, NET, SG, UBS, DB, and SWB). Each regression also contains 189 stock fixed effects to control for heterogeneity in unconditional order usage rates across stocks.

Table IA.II
Logit Regressions of Investors' Limit Order-Market Order Choice on the State of the Market

This table reports on logit regressions estimated using data simulated from the dynamic limit order book model of Goettler, Parlour, and Rajan (2009) (Panel A) and actual microstructure data from the Helsinki Stock Exchange (Panel B). I parameterize the model by assuming that one-half of all traders acquire information about the asset and that (independently) one-half of all traders have a lower discount rate (i.e., higher patience) than the other half. All other parameters are from Goettler, Parlour, and Rajan's (2009) high-volatility regime specification. I numerically find the equilibrium and then simulate a further 2.1 million entries into the market, including reentries by traders who have previously arrived at the market. I discard the first 0.1 million entries to burn in the market. The dependent variable takes the value of one if a trader submits a limit order and zero if the trader submits a market order. The regressors characterize the state of the market and are measured an instant before each trader arrives. These variables are the natural logarithm of the bid-ask spread and its squared value, the change in the bid-ask spread from five minutes ago, the signed change in the midpoint of the bid-ask spread from five minutes ago (i.e., $\ln(\mathrm{mp}_t/\mathrm{mp}_{t-5\mathrm{min}})$ for buy orders and $-\ln(\mathrm{mp}_t/\mathrm{mp}_{t-5\mathrm{min}})$ for sell orders), the natural logarithm of the number of market order arrivals on the same side (opposite side) of the market during the preceding five-minute period (plus one), and the natural logarithm of the number of limit order arrivals on the same side (opposite side) of the market during the preceding five-minute period (plus one). Panel A reports on the logit regressions that use simulated data. I partition the sample based on trader attributes. These attributes include information status, the patience parameter, and the realization of the private component of the asset's value ("Private v"). The bottom rows in each regression block report the pseudo R^2, the trader group's unconditional limit order usage rate, and the number of observations. Panel B reports on analogous regressions, which I estimate by using actual microstructure data from the Helsinki Stock Exchange from September 18, 1998 through October 23, 2001. Both Panel B regressions include 189 (unreported) stock fixed effects. "Individual investors" are the two most household-intensive brokers in the data. "Institutional investors" are the eight most institution-intensive brokers in the data.

Panel A: Logit Regressions using Simulated Data									
Trader Type	Explanatory Variable	All Private v		Private $v = 0$		$\lvert$Private $v\rvert = 4$		$\lvert$Private $v\rvert = 8$	
		$\hat{b}$	z	$\hat{b}$	z	$\hat{b}$	z	$\hat{b}$	z
Patient Informed Traders	Bid-Ask Spread	30.460	132.24	36.525	96.48	24.409	59.06	41.773	80.45
	100 $*$ (Bid-Ask Spread)^2	−0.548	−73.86	−0.667	−55.15	−0.370	−26.53	−0.821	−50.96
	Δ(Bid-Ask Spread)	0.187	2.75	−0.256	−2.34	−0.083	−0.68	0.838	5.69
	Signed Δ(Spread Midpoint)	16.298	180.98	21.615	140.31	17.534	109.59	16.438	82.27
	Market Orders, Same Side	−1.327	−20.89	−1.190	−11.85	−1.917	−17.04	−1.854	−13.32
	Market Orders, Opposite Side	1.063	10.85	0.869	5.57	1.611	9.33	1.534	7.20
	Limit Orders, Same Side	0.506	10.86	0.273	3.77	0.750	8.94	0.186	1.75
	Limit Orders, Opposite Side	0.347	3.15	0.539	3.17	0.297	1.49	1.389	5.44
	Pseudo R^2	0.183		0.230		0.184		0.242	
	Limit Orders (%)	81.35%		85.24%		81.82%		69.31%	
	N	439,917		215,167		149,235		75,515	
Impatient Informed Traders	Bid-Ask Spread	26.414	111.29	20.930	47.16	41.264	93.60	44.998	77.05
	100 $*$ (Bid-Ask Spread)^2	−0.438	−55.64	−0.256	−16.40	−0.764	−55.50	−0.836	−47.08
	Δ(Bid-Ask Spread)	1.076	15.32	0.338	2.65	0.994	7.72	1.527	9.32
	Signed Δ(Spread Midpoint)	12.501	136.55	20.246	112.56	16.260	94.22	18.109	80.49
	Market Orders, Same Side	−1.211	−18.38	−1.288	−11.29	−1.651	−13.69	−1.801	−11.46
	Market Orders, Opposite Side	0.900	8.87	0.757	4.26	1.162	6.29	1.283	5.34
	Limit Orders, Same Side	0.747	15.17	1.077	12.85	0.531	5.79	0.406	3.44
	Limit Orders, Opposite Side	0.114	0.97	−0.351	−1.81	0.876	3.98	0.685	2.41
	Pseudo R^2	0.166		0.200		0.252		0.308	
	Limit Orders (%)	70.56%		82.82%		68.73%		44.74%	
	N	301,603		140,256		101,932		59,415	

	Bid-Ask Spread	27.612	127.94	20.029	51.55	47.894	108.50	50.305	94.42
	100 ∗ (Bid-Ask Spread)^2	−0.493	−68.51	−0.266	−19.03	−0.942	−69.35	−0.988	−61.29
	Δ(Bid-Ask Spread)	0.057	0.93	−0.164	−1.60	0.535	4.28	1.305	8.60
Patient	Signed Δ(Spread Midpoint)	9.072	119.67	15.506	120.54	14.311	87.10	13.322	68.18
Uninformed	Market Orders, Same Side	−0.670	−11.34	−0.849	−8.34	−0.701	−5.99	−0.974	−6.86
Traders	Market Orders, Opposite Side	0.589	6.46	0.782	4.98	−0.032	−0.18	0.230	1.05
	Limit Orders, Same Side	0.370	8.79	0.524	7.62	−0.045	−0.52	−0.050	−0.45
	Limit Orders, Opposite Side	0.608	6.15	0.385	2.46	1.833	8.72	2.117	7.95
	Pseudo R^2	0.117		0.137		0.244		0.286	
	Limit Orders (%)	85.74%		93.43%		77.35%		59.09%	
	N	575,215		378,860		126,848		69,507	
	Bid-Ask Spread	20.444	95.72	25.590	60.14	48.290	103.22	52.878	79.51
	100 ∗ (Bid-Ask Spread)^2	−0.319	−43.11	−0.419	−28.93	−0.925	−65.61	−0.956	−49.28
	Δ(Bid-Ask Spread)	0.735	12.19	0.230	1.93	1.103	8.35	1.838	10.05
Impatient	Signed Δ(Spread Midpoint)	5.717	77.70	14.996	99.51	14.189	82.08	15.773	66.28
Uninformed	Market Orders, Same Side	−0.637	−11.11	−0.704	−6.18	−0.679	−5.37	−1.369	−7.85
Traders	Market Orders, Opposite Side	0.672	7.59	0.448	2.54	−0.207	−1.07	0.646	2.41
	Limit Orders, Same Side	0.430	10.09	0.643	8.19	−0.115	−1.18	−0.025	−0.18
	Limit Orders, Opposite Side	0.446	4.42	0.378	2.12	2.075	8.91	2.090	5.96
	Pseudo R^2	0.093		0.146		0.296		0.370	
	Limit Orders (%)	74.29%		91.51%		52.60%		34.15%	
	N	387,413		242,820		87,863		56,730	

Panel B: Logit Regressions using HEX Microstructure Data				
Explanatory	Individual Investors		Institutional Investors	
Variable	$\hat{b}$	z	$\hat{b}$	z
Bid-Ask Spread	41.974	89.00	66.845	66.28
$100 * (\text{Bid-Ask Spread})^2$	−0.484	−12.09	−2.782	−19.92
Δ(Bid-Ask Spread)	1.392	4.36	34.299	57.24
Signed Δ(Spread Midpoint)	9.971	38.06	8.194	26.66
Market Orders, Same Side	−0.568	−168.59	−0.674	−225.51
Market Orders, Opposite Side	0.161	47.56	0.164	56.84
Limit Orders, Same Side	0.216	64.06	0.446	144.03
Limit Orders, Opposite Side	0.139	38.95	0.071	23.03
Pseudo R^2	0.054		0.049	
Limit Orders (%)	72.39%		53.01%	
N	1,749,206		1,854,533	

Both individuals and institutions respond to changes in market conditions in much the same way as the simulated traders. Investors are more likely to submit limit orders when the spread is wide or has just widened, when the bid-ask spread midpoint has moved away from the trader, and when the flow of market orders on the opposite side of the market has been high. The effect of the bid-ask spread on the limit order choice is also concave in both simulations and actual data. A comparison of individual and institutional investors suggests that institutions are far more responsive to variation in the three state variables that is related to the size of the bid-ask spread. By contrast, individuals and institutions respond quite similarly to changes in the other state variables.

In simulations, traders who are uninformed, more patient, or whose private value component realizations are closer to zero use more limit orders. Of these three channels, the private value component has the strongest effect and variation in this dimension can generate a remarkably good match between the data and the simulations. If institutions tend to receive larger draws of the private value component, then differences in individual investors' and institutional investors' order usage rates and sensitivities to market conditions conform to the simulations. Variation in this dimension could explain, first, why individual investors use more limit orders in general and, second, why institutions are more sensitive to changes in the bid-ask spread.

The conclusion that the private component channel can explain institutions' and individuals' order choices is intriguing. The model does not need to bombard individual investors with extreme liquidity shocks to get them to trade. Instead, this result suggests that individual investors may be, in the language of the model, uninformed traders with private value components close to zero. Such traders enter the market because they expect to gain from the liquidity demand of impatient investors with large private value component realizations. This characterization of individual investors is consistent with Kaniel, Saar, and Titman's (2008) conclusion that individual investors provide liquidity to meet institutional demand for immediacy.

The central role of the private value component also reflects the idea that we expect institutions to experience larger shocks to this component. For example, if many mutual fund investors redeem their shares simultaneously, then the fund has to sell some of its holdings very quickly. In the model redemption and inflow shocks are represented by shocks to the private value component. An increase in the absolute size of this component increases the reward for executing an order. If individual investors have more discretion, relative to institutional investors, over the timing of their purchases and sales, then individual investors' private value component shocks have lower variance.

Both the comparative statics and the full-fledged dynamic limit order book model suggest that individual investors' order choices do not deviate significantly from theoretical predictions. Moreover, individual investors' order choices can best be explained under a plausible scenario: individual investors are uninformed traders who enter the market to profit from other investors' demand for immediacy.

II. The Long-lasting Momentum in Weekly Returns in Finland

Figure IA.1 replicates Gutierrez and Kelley's (2008) Figure 1 on momentum in U.S. weekly returns, using Finnish return data.

The data are the dividend and split-adjusted prices from Datastream from January 1995 through May 2009. I compute weekly returns from Wednesday to Wednesday. I use the midpoints of the quoted bid and ask prices at each day's close (when available) to avoid spurious reversals. I exclude all stocks with market values below €10m at the end of formation week t to avoid extremely illiquid stocks. I compute raw profits for each separate event week. Figure IA.1 plots the cumulative profits.

The pattern in Figure IA.1 is remarkably similar to the pattern that Gutierrez and Kelley (2008) find for U.S. stock returns. Stock returns reverse significantly one week after extreme returns and move slightly against the long-short portfolio for another week. The momentum portfolio begins a persistent run-up in profits three weeks after the portfolio formation date. The reversal pattern almost entirely corrects itself 12 weeks after the portfolio formation date. By the end of the year, the long winners-short losers portfolio is up by 2.3%.

Gutierrez and Kelley (2008) also use the Jegadeesh and Titman (1993) method for a formal statistical analysis that avoids overlapping returns. They first form the long-short momentum portfolio for each week t_0 and then compute one-week returns, $r_{t_0+k|t_0}$, for week $t_0 + k$. I compute the portfolio returns for each holding period without overlap by forming a calendar-time portfolio that rebalances a fraction $\frac{1}{T}$ of the portfolio each day. For example, if the holding period is from week 4 to week 52 (i.e., skip three weeks and then hold the portfolio for 49 weeks), I compute the portfolio return for week t by averaging over returns on 49 different strategies, $r_t^p = \frac{1}{49}\sum_{k=4}^{52} r_{t|t-k}$. When I apply this method to the data, the annualized return for week one is -54.1% ($t = -7.8$). This average is close to the estimate of -70.6% in Gutierrez and Kelley (2008).

The annualized returns for the other permutations in Gutierrez and Kelley (2008), Table I are as follows: week two = -0.7% ($t = -0.1$); week three = 1.3% ($t = 1.3$); weeks 4 to 52 = 3.4% ($t = 2.6$); and weeks 1 to 52 = 2.3% ($t = 1.8$). These returns are qualitatively similar to the returns reported in Gutierrez and Kelley (2008) for the U.S. stock market. The notable differences are that first, the reversal in Finland lasts for only one week instead of two, and second, the longer holding period returns are higher in the U.S. than they are in

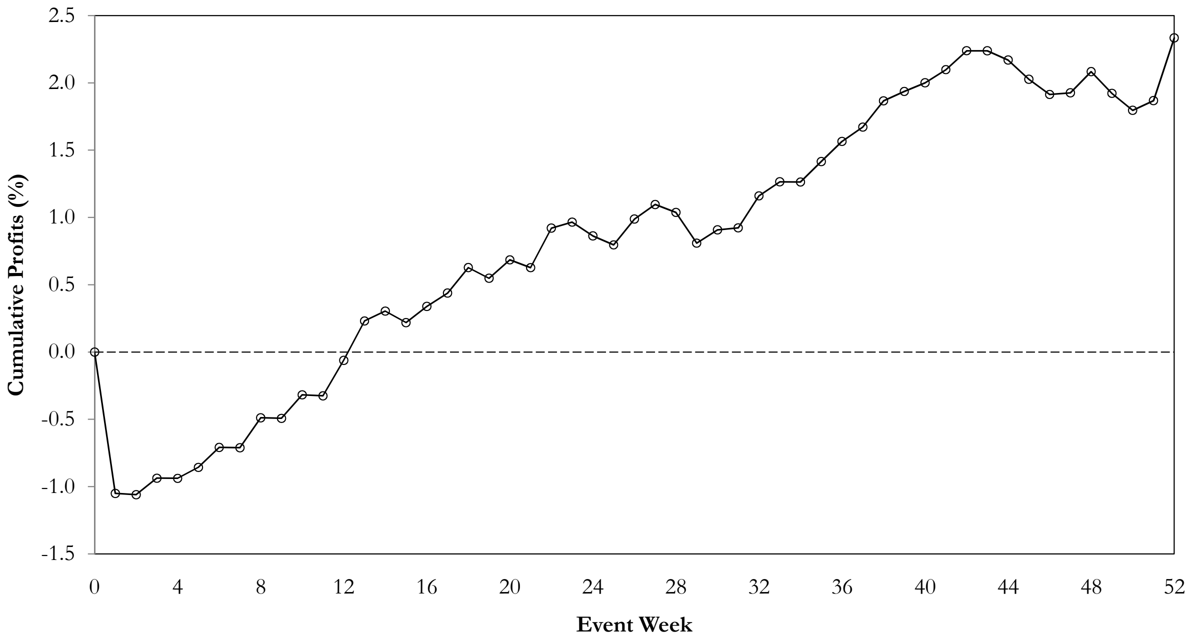

Figure IA.1. The long-lasting momentum in weekly returns. This figure replicates Gutierrez and Kelley's (2008) Figure 1 on long-lasting momentum in weekly returns, using Finnish return data. Each week from January 1995 through May 2009, I rank stocks based on their returns over the prior week and form a portfolio comprised of a long position in the top decile of stocks (winners) and a short position in the bottom decile (losers). I calculate raw profits for each separate event week and plot cumulative profits. I compute weekly returns from Wednesday to Wednesday, using the midpoints of the quoted bid and ask prices at each day's close (when available). I exclude stocks with market values below €10m at the end of formation week t.

Finland. Gutierrez and Kelley (2008) report average returns of 8.1% and 5.1% for holding periods corresponding to weeks 4 to 52 and weeks 1 to 52, respectively.

These estimates indicate that the return pattern documented in Gutierrez and Kelley (2008) for the U.S. stock market, "the long-lasting momentum in weekly returns," is also apparent in the Finnish stock market from January 1995 through May 2009.

III. Do Limit Orders Alter Inferences about The Disposition Effect in U.S. Data?

Because individual investors in the U.S. use limit orders extensively, inferences drawn from U.S. data about investor behavior, such as disposition effect estimates, may also reflect the limit order effect. I examine the effect on disposition effect estimates using account data for over 35,000 households from a large U.S. discount broker from February 1991 through November 1996. (My sample is restricted to those households for which demographic data are available.) These same data have been used by Barber and Odean (2001), Kumar and Lee (2006), and others. Importantly, these data do not show investors' order choices. However, a testable implication of the limit order effect is that, if some trades originate from limit orders,

Table IA.III
The Disposition Effect in U.S. Data: PGR and PLR Analysis

This table compares the aggregate proportion of losses realized (PLR) to the aggregate proportion of gains realized (PGR). PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains; similarly, PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. Realized gains, paper gains, realized losses, and paper losses are aggregated over 35,000 households from a large U.S. discount broker from February 1991 through November 1996. These data are used in Barber and Odean (2001). The proportions are computed both for the full sample as well as for three subsamples that are based on the same-day stock price movement: days when the stock price falls by at least 2% (L), days when the stock price rises by at least 2% (H), and days when the stock price stays within 2% of the previous closing price (M). The stock returns are taken from the daily CRSP tapes. t-values are computed under the assumption that all observations are independent. The first row reports the original PLR-PGR results from Odean (1998, Table 1) for reference.

	Number of					
Sample	Gains	Losses	PLR	PGR	PLR-PGR	t-value
Odean (1998)	93,541	122,278	9.76%	14.84%	−5.09%	−35.3
Barber and Odean (2001)						
Full Sample	2,946,229	2,191,895	8.78%	12.62%	−3.85%	−141.5
L: $r_{it} \leq -2\%$	1,202,465	1,079,098	9.39%	11.20%	−1.82%	−45.2
M: $-2\% < r_{it} < 2\%$	325,374	335,070	7.58%	10.35%	−2.77%	−39.4
H: $r_{it} \geq 2\%$	1,418,390	777,727	8.45%	14.35%	−5.90%	−136.9
L minus H			0.94%	−3.15%	4.09%	69.3
M minus Full Sample			−1.20%	−2.27%	1.07%	14.3

then disposition effect estimates should be sensitive to same-day stock price movements. More sell limit orders execute on days when the stock price rises than on days when the stock price falls. The resulting differences in limit order execution rates should influence disposition effect estimates because a stock sale on a down day more likely originates from a market order.

Table IA.III replicates the PGR-PLR methodology of Odean (1998) conditional on same-day stock price movements. This methodology computes the proportion of losses realized (PLR) and the proportion of gains realized (PGR), and uses the difference as a measure of the disposition effect. Paper gains and losses are computed every time an investor sells something from her portfolio. A negative PGR-PLR value indicates that investors realize more gains, consistent with the disposition effect.

I measure the sensitivity of disposition effect estimates to same-day stock price movements by computing PGR and PLR conditional on the same-day return on the stock that is sold. I split the sample into three categories based on the size of the same-day stock price movement: the stock price falls by at least 2%, the stock price increases by at least 2%, and the stock price stays within the (−2%, 2%) range. The disposition effect estimate is predicted to be the highest in the high return category ($r_{it} > 2\%$) because, if individual investors use limit orders, then this category contains most sell limit order executions. However, the disposition effect estimate may also be higher in the high return category because a higher stock price implies that a stock is more likely a "winner" than a "loser." For this reason, in addition to conducting a high-minus-low comparison, I also compare full sample estimates to the estimates from the middle return category ($-2\% < r_{it} < 2\%$). The average gains in these categories should be the same by symmetry, that is, $(-\infty, +\infty)$ versus $(-2\%, +2\%)$. But if investors' use of limit orders contributes to inferences about the disposition effect, then the disposition effect estimates should differ between these two categories. The reason is that sell limit orders are more likely to execute when the same-day return takes more extreme values. Thus, the full sample should contain relatively more limit order sales than the medium-return category.

Consistent with the limit order mechanism, Table IA.III shows that the estimated disposition effect is significantly stronger on up days than on down days: the PLR-PGR difference is -1.82% on days when the stock that is sold has a negative same-day return but -5.90% when the stock that is sold has a positive same-day return. The difference-in-difference between the high category and the low category is 4.09% (t-value = 69.3). The change in the PLR-PGR statistic is largely due to the change in the proportion of gains realized (-3.15%) and not to the change in the proportion of losses realized (0.94%). This finding supports the argument that fewer sell limit orders execute when the stock price falls.

The more conservative comparison between the middle return category ($-2\% < r_{it} < 2\%$) and the full sample also supports the existence of the limit order effect in the U.S. data. The PLR-PGR difference is 1.07% higher in the middle return category compared to the PLR-PGR difference in the full sample. The t-value for this difference is 14.3. This difference supports the hypothesis that by moving from the full sample to the medium return sample, sell limit order execution rates decrease. The estimates in Table IA.III support the possibility that individual investors' use of limit orders alters inferences about investor behavior also in the U.S. markets.

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