Financial Attention

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Abstract

This paper investigates investor attention using novel panel data on daily online logins for a large sample of retirement accounts. We find support for selective attention to portfolio information. Account logins fall by 9.5% after market declines. Investors also pay less attention when the VIX volatility index is high. The level of attention and the attention/return correlation are strongly related to investor demographics (gender, age) and financial position (wealth, holdings). Using a new statistical decomposition, we also show how aggregate and individual household trading are related to investor attention.

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Attention by investors to their portfolios plays a dual role in financial markets. It is an input into decision-making for trading and risk-bearing and also a cognitive pathway through which investors experience and derive utility. This dual role raises a variety of questions: When and under what conditions do investors pay attention to their portfolios? What does attention behavior reveal about investor demand for information? To what extent is attention driven by hedonic effects of information? What accounts for differences in attention across individual households? And how does investor attention behavior affect trading? Our paper answers these questions in the first large-scale empirical study of investor attention to their personal portfolios. In doing so, we identify new properties about both the market factors and demographic characteristics that drive attention and about the relationship between attention and trading.

Our understanding of the different roles of attention draws on several lines of research. The literature on rational inattention posits that attention is costly, and that investors only pay attention given a positive cost-benefit trade-off (Sims 2003). The costs of attention include information-processing costs and time and opportunity costs, while a benefit of financial attention is the potential gains from trading.[1] The literature on information-dependent and belief-dependent utility posits, however, that information also has a hedonic impact on utility that goes beyond mechanical costs and benefits (e.g., Loewenstein, 1987; Caplin and Leahy 2001; Brunnermeier and Parker 2005). The hedonic impact of unfavorable and favorable information creates, in turn, incentives to avoid or pay attention to information. Absent such hedonic effects, the standard economic account of information predicts that costless information should never be deliberately avoided since information always weakly improves decision-making. However, the literature on selective attention shows that, in many situations, people do avoid information that would be useful in decision-making (Ehrlich et al. 1957, Frey and Stahlberg 1986, Lyter et al. 1987, Witte 1998, Caplin and Eliaz 2003, Köszegi 2003, 2010, Thornton 2008, and Oster, Shoulson and Dorsey 2013).

One specific form of selective attention is the *ostrich effect* introduced by Karlsson, Loewenstein, and Seppi (2009). They propose that attention amplifies the hedonic impact of

[1] Research on information processing limits in finance includes Barber and Odean (2008) on attention-grabbing for individual stocks and Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2009) on limited attention to accounting disclosures.

information, which implies that investors should pay more attention to their finances after good news than after bad news.[2] In particular, attention to investors' personal portfolios should increase after positive returns on market indices. The idea is similar to realization utility (Barberis and Xiong 2012, Ingersoll and Jin 2013, and Imas 2014) in which trading produces a magnified burst of utility—i.e., realized gains and losses cause greater utility swings than paper gains and losses—except that now it is *looking* (rather than trading) that produces a burst of utility. Both the ostrich effect and realization utility share a common underlying psychological mechanism in that investor actions (paying attention or trading) intensify the hedonic impact of information. Selective attention to portfolio information may also depend on other factors such as market volatility and news media coverage.

The digitization of the investment process and the attendant tracking of online behavior allow direct measurement of investor attention in ways that previously were not possible. Our analysis follows Karlsson et al. (2009) in using online account logins to measure investor attention to their portfolios.[3] Using a large panel data set on daily logins for retirement accounts over the two-year period 2007-2008, we document a number of patterns in investor attention and market conditions:

- Investors log in to pay attention to their portfolios much more often than they trade. This suggests investors get hedonic utility from attention to, or avoiding, information about their portfolio.
- The ostrich effect operates at daily, weekly and monthly return horizons and is robust to a variety of specifications.
- Investor attention is decreasing in the VIX index as a measure of expectations about future stock volatility. We call the negative correlation of attention with volatility the *volatility ostrich effect*. Financial market reporting by the news media also attracts investor attention.

We also document demographic patterns in investor attention:

- The average level of attention and the strength of "ostricity" are greater in males and in wealthier investors.

[2] This behavior could be motivated by a desire to maintain optimism (as in the optimal beliefs model) or to preserve a positive self-image as a good investor.
[3] Our account-login metric is similar to the Google search metric in Da, Engelberg, and Gao (2011) except that our focus is on attention to personal portfolios rather than to individual stocks. Our attention metric also differs from the FEARS search index in Da, Engleberg and Gao (2015), which measures fluctuations in investor sentiment.

- Investors who hold more bonds than equity display weaker ostrich behavior. At the extreme, investors holding only bonds actually pay more attention when the stock market is down than when it is up. We argue this pattern is strongly consistent with hedonic effects in attention.
- Ostrich behavior in individual investors in 2007 is correlated with ostrich behavior in 2008. This suggests that ostricity is a stable personal characteristic over time.[4]

Investor attention is important in financial markets in part because attention affects trading. Trading has been studied extensively (Karpoff 1987, Chordia, Roll, and Subrahmanyam 2001, Griffin, Nardari, and Stulz 2007, Glazer and Weber 2009). However, our data allow us to decompose patterns in trading into deeper underlying patterns in attention (i.e., the demand for information) and in what we call *conditional trading*. Conditional trading—which we measure as the daily fraction of logged-in accounts that also trade—is an attention-adjusted measure of the decision to trade. In other words, it measures trading after controlling for the decision to pay attention. Using this decomposition, we find that

- Trading is discontinuous and non-linear in lagged returns due to opposing patterns in attention and conditional trading. Conditional trading is generally decreasing in lagged returns, whereas attention is generally increasing for a wide range of lagged returns.
- Trading and news media stock market coverage are positively correlated due to both attention and conditional trading.
- Attention and conditional trading move in opposite directions with the VIX, with the net effect on trading being ambiguous.

These findings suggest new insights into the behavioral drivers of trading. For example, the increased conditional trading in down markets is consistent with bargain-hunting and stop-loss strategies but is inconsistent with trading-based realization utility bursts. In addition, trading confidence (i.e., increased trading induced by positive returns) appears to operate through the attention channel than through conditional trading. In particular, investors are empirically more

[4] Empirical evidence on the stability of time and risk preferences and other personal characteristics is mixed. See Dohmen et al. (2011), Meier and Sprenger (2010), and Rick, Cryder and Loewenstein (2008).

engaged in financial markets after they experience favorable returns (in the sense that they pay more attention), whereas trading is inversely related to prior returns after controlling for attention.

Attention is also important as a micro-foundation of household finance (see Campbell 2006 for a review of the previous literature). After documenting demographic differences in household attention, we use our panel data to decompose demographic patterns in trading into underlying demographic patterns in attention and conditional trading. For example, previous research finds that women trade less than men, a pattern that has been attributed to male overconfidence (Barber and Odean 2001). We find that the gender difference in trading is due both to lower financial attention in women and to less conditional trading once women log in. The former could be due to differences in competing household demands, financial education, and interest in score-keeping, while the latter is consistent with differences in confidence. In addition, a stronger ostrich effect in males may contribute to greater average trading confidence since males pay less attention in down markets when equity in their portfolios performs poorly. We also show that ostrich and non-ostrich investors trade differently. Specifically, individuals identified as ostrich investors tend, as a group, to trade less in down-markets. Hence, although the ostrich effect deprives investors of information in some situations, it may be a beneficial behavioral adaptation if it helps them to avoid trading mistakes such as overreacting to market downturns.

There is a growing theoretical recognition that investor attention behavior can affect asset pricing (see Andrei and Hasler 2015). Our empirical findings have two specific implications for asset pricing. First, our results provide novel and strong micro-evidence of information-dependent utility in individual investors. In particular, the investor behavior we observed is consistent with the idea that investors get utility directly from information as well as from consumption.[5] Information-dependent utility is an important topic in current asset pricing research. In particular, research based on Epstein and Zin (1989) recursive preferences—which are a particular form of information-

[5] Information-dependent utility means that investor marginal utility $u'(c_t\ I_t)$ depends directly on market information I_t as well as on current consumption c_t. This is in contrast to the consumption utility framework in which marginal utility $u'(c_t)$ depends only indirectly on information I_t via its effect on consumption c_t through the consumption and portfolio choice decisions. Consequently, the MRS $u'(c_{t+1,}\ I_{t+1})/u'(c_t, I_t)$, which is what matters for asset pricing with information-dependent utility, depends directly on information as well as indirectly through the endogenous consumption process.

dependent utility—shows that changes in information can change the preferences implicit in the market pricing kernel in ways that help explain significant asset pricing anomalies.[6]

Second, our results about time-variation in the tendency of investors to login imply that investor information-timing preferences fluctuate over time. This follows because logins are a direct measure of investor preferences for the timing of information revelation. Simply put, logging in signals a revealed preference for getting information earlier rather than later. One reason this matters for asset pricing is that information-timing preferences are linked with the so-called volatility risk premium and, specifically, with option pricing. With recursive utility, for example, expected returns on call and put options—which are long volatility and, thus, which can function as volatility hedges—are predicted to be lower when investors have a preference for early resolution of uncertainty (see Boguth and Kuehn 2013).[7] Thus, the ostrich effect indicates an underlying preference for early resolution of uncertainty and, therefore, a lower volatility risk premium in rising stock markets. Similarly, the volatility ostrich effect implies a preference for late information and a higher volatility risk premium when future stock market volatility is expected to be high. In contrast, the direction of Epstein-Zin information-timing preferences is constant over time.[8] Thus, our results suggest new directions for asset pricing modeling.

I. Theoretical motivation and predictions

Our investigation of attention has several motivations. Our first motivation is that patterns in attention are a window into information-dependent utility. Karlsson, et al. (2009) presents a decision-theoretic model of optimal attention for investors whose utility depends, in part, directly on information. Investors feel good when their portfolio increases in value and bad when its value drops, and

[6] See the Backus, Zin, and Routledge (2004) survey and Benartzi and Thaler (1995), Gneezy and Potter (1997), Barberis, Huang, and Santos (2001) and the large literature based on the Bansal and Yaron (2004) long-run risk model. One important feature to note is that the information learning process is exogenous in these models, whereas the ostrich effect is about *discretionary* information acquisition decisions.
[7] A preference for early resolution of uncertainty means investors prefer learning information sooner rather than later.
[8] Epstein-Zin information-timing preferences depend on the relative sizes of the intertemporal elasticity of substitution and the coefficient of relative risk aversion. Thus, depending on which of these two parameters is larger, Epstein-Zin attention decisions should be consistently in the same direction; namely either to always ignore or to always pay attention. One possible interpretation of our findings that information-timing preferences change is that the intertemporal elasticity of substitution and risk aversion actually change over time.

attention amplifies the hedonic impact of information. As a result, investors make attention decisions in part to manage their psychological exposure to positive and negative information. Specifically, they should be more likely to log in to check their account when past returns suggest that attention is likely to reveal good news rather than bad news. This behavior leads to a prediction called the ostrich effect:[9]

Hypothesis H1: Investors holding equity pay more attention to their investments in rising stock markets than in falling markets.

An alternative is that bargain-hunting could increase investor attention after negative returns. It is also possible that general curiosity and monitoring for potential trading opportunities can induce a U-shaped relationship between attention and past returns after large price swings.[10]

Karlsson et al. (2009) find empirical support for the ostrich effect using weekly market index returns and aggregate data on daily total account logins at an American investment company (Vanguard) and from the Swedish Premium Pension Authority. Eil and Rao (2011) and Sharot et al. (2012) also find experimental and neuroscience support for the ostrich effect. However, Gherzi, Egan, Haisley, and Ayton (2014) find mixed results for a small sample of survey respondents. Our analysis extends the weekly return analysis in Karlsson et al. (2009) by including daily, weekly and monthly returns and by allowing for nonlinearities, and our sample is much larger than in Gherzi et al. (2014).

We generalize the ostrich effect to allow portfolio attention to depend on other market factors. Andries and Haddad (2013) predict that attention should decrease in volatility for loss-averse investors. A related idea is that investors may emotionally disengage from the market in advance of periods in which they are worried about the risk of extreme outcomes. We call a negative correlation between attention and volatility the volatility ostrich effect. In addition, news media coverage of the stock market may act as a market analogue to stock attention-grabbing (Barber and Odean 2008).

[9] See also Golman and Loewenstein (2012). Galai and Sade (2006) use the term "the ostrich effect" differently from us to mean a general preference for delayed information rather than a changing conditional preference.

[10] The qualifier "potential" is significant given the low level of actual trading relative to logins. Simply eliminating logins associated with trades would not necessarily purge the login data of potential trading motives.

Hypothesis H2: Information utility effects cause attention to decrease in market volatility.

Hypothesis H3: Attention increases in news media coverage of the stock market.

The second motivation for our investigation of attention is to understand the impact of attention on trading. The new idea is that trading can be decomposed into an attention decision and a separate decision to trade conditional on paying attention. The former is driven by a demand for information, while the latter is a "pure" or "post attention" trading decision that takes the attention decision as given. Aggregate trading combines patterns in both components. A new feature of our analysis is that we identify behavioral motives for these two components of trading separately.

Since we have data on both trading and account logins, we can measure how many investors decide to pay attention and how many then decide to trade given that they are paying attention. Let NT_t denote the number of investor accounts with trades on day t, let NL_t denote the number of accounts with logins on day t, and define the conditional trading variable CT_t as the fraction of accounts that, conditional on having logged in on day t, then trade on date t. These three variables are related by the identify $NT_t = NL_t \cdot CT_t$, which can be rewritten as

$$(1) \qquad \ln(NT_t) = \ln(NL_t) + \ln(CT_t)$$

Regressing $\ln(NT_t)$ on a set of explanatory factors, X_t, lets us identify patterns in observed trading. These patterns can then be decomposed into separate patterns in attention (by regressing $\ln(NL_t)$ on X_t) and in conditional trading (by regressing $\ln(CT_t)) = \ln(NT_t) - \ln(NL_t)$ on X_t). Patterns in logins reflect attention behavior driven by information utility bursts, such as the ostrich effect, as well as by monitoring for potential trading opportunities. In contrast, conditional trading is, by definition, purged of the effects of changes in attention. Positive feedbacks between lagged returns and conditional trading are consistent with realization utility bursts (as gains and losses are definitively "booked") and fluctuations in investor confidence (Daniel, Hirshleifer, and Subrahmanyam 1998; Gervais and Odean 2001), while a negative correlation can be caused by stop-loss trading and bargain hunting. Optimal tax loss realization is not a consideration in this study, since our sample consists of tax-exempt accounts.

Hypothesis H4: Patterns in aggregate attention and conditional trading differ due to differing underlying economic drivers.

A third motivation for our research is that attention is a part of financial decision-making by individual households. Our panel data allow us to investigate demographic patterns in the ostrich effect and other attention behavior in individual investors on a large scale. Differences in attention across individuals may, for example, reflect differences in the emotional salience of retirement investment information given their position in the lifecycle and their wealth.[11] We also investigate the sources of demographic patterns in trading (e.g., gender differences in Barber and Odean 2001).

Hypothesis H5: The average level of attention and ostrich effect behavior are greater for older investors (closer to retirement) and for wealthier investors for whom hedonic information effects are likely to be stronger.

Hypothesis H6: Household attention and conditional trading have different demographic patterns.

Even though our two-year sample is too short to investigate the asset pricing implications of attention, we do study how attention, trading, and risk-bearing interact. Ostrich behavior may, for example, be associated with increased ex ante risk-bearing (as an adaptive response to greater risk). Prior research (Barber and Odean 2001; Zeckhauser and Niederhoffer 1983) also suggests that retail investors make systematic trade timing mistakes by moving out of equities after prices drop and failing to move back before prices recover. To the extent that the ostrich effect mitigates such

[11] Hirshleifer and Shumway (2003), Goetzmann, Kim, Kumar, and Wang (2015), and Edmans, Garcia, and Norli (2007) study the emotion-based impact of weather and sport outcomes on financial markets. Our results suggest attention as another channel through which emotions enter financial decision-making.

counter-productive trading behavior—since investors who do not pay attention in down markets cannot trade in down markets—the ostrich effect might actually be beneficial.[12]

Hypothesis H7: Ostrich behavior is positively correlated with greater equity risk-bearing.

Hypothesis H8: Investors displaying the ostrich effect trade less in down stock markets.

II. Account data

Our analysis uses detailed panel data on 1,168,309 defined-contribution retirement accounts over 2007-2008. The data were provided by Vanguard, the account record-keeper, on an anonymous and secure, restricted-access basis. These accounts are mostly 401(k) accounts, but also some money purchase pension plans, profit-sharing plans, a few ESOP accounts (i.e., employer stock only), and 403(b) plans (e.g., universities). Retirement accounts are a growing fraction of household financial wealth and an important subject for research on household financial behavior. Our data include information on

- Daily account activity: One observation per account per day on the number of times individual investors logged in to their account and also on whether they traded.
- Monthly account information: One observation per account per month of the end-of-month account balance and account composition (percentage of stocks versus bonds).
- Demographics: One observation per account about personal account-holder characteristics.

Given the large size of the full data set (2 years x 365 daily observations per account per year x 1,168,309 accounts = 852,865,570 login observations), our analysis focuses on a randomly selected subsample of 100,000 "paperless" accounts. The owners of these accounts do not receive quarterly paper statements in the mail, so their online logins provide a more complete record of attention to their personal portfolios than the logins of investors who also receive quarterly statements by mail. A maintained assumption here is that when investors log in to check their portfolio, they are paying attention to that information.

[12] The ostrich effect is beneficial if it helps keep investors from selling after short-term downturns (given negative autocorrelation in daily and weekly returns), but it can be harmful at longer horizons (given positive momentum in longer returns). Also, our data only indicate when investors traded, not what they bought or sold on any given day.

Table 1 provides an overview of the 100,000 paperless accounts and a comparison with the full sample of all 1.2 million accounts. Investors in the two samples are demographically similar. On average, they are in their mid-40s, about one third are female, and they have portfolios strongly weighted towards equity. It should be emphasized that we study attention of "ordinary" individual investors. We would expect different attention behaviors for institutional portfolio managers and day-traders.[13]

1. Distribution of logins and trading

Figure 1 shows the cross-sectional distribution of the total number of days logged-in per account across the 100,000 paperless accounts over the full 2007-2008 sample period. Not surprisingly, there is considerable heterogeneity in login frequency across investors. Over this two-year period, approximately 2.7% of the investors in the sample never logged in, 2.4% logged in only once, while 4.2% logged in on more than half of the trading days. For most investors, logging in to their retirement account is an activity that occurs with sufficient frequency that we may safely assume they know how to do it, but it is not an automatic daily routine. Since logging in appears to be a decision rather than a default, it is reasonable to examine what causes investors to log in.

Table 2 reports cross-sectional distributions (across accounts) for the number of days with logins and days with trading. Trading is very infrequent compared to logins, which implies that the average conditional trading ratio (discussed in Section I) is low. Figure 2 plots the daily number of accounts that engaged in trading versus the corresponding daily number of accounts with logins (trimmed to exclude the 1% most extreme outliers). The figure also shows fitted means for the daily number of accounts with trades conditional on the daily number of accounts with logins (the solid line) and 95% confidence intervals as estimated using Symmetric Nearest Neighbor Smoothing.[14] As expected, there is a positive relationship between logins and trading, but the correlation is far from lockstep.

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[13] See Corwin and Coughenour (2008), Foucault, Röell, and Sandås (2003), Simon and Heimer (2012), and Kacperczyn, van Nieuwerburgh, and Veldkamp (2014).

[14] See Cleveland (1979). This procedure translates a scatter-plot into a smooth line by fitting simple models to localized subsets of the data to build up a function that describes predictable variation in the data point by point. This method does not require a priori specification of a global function to fit a model to data. It also provides a 95% confidence interval.

Taken together, the low level of trading relative to logins (Table 2) and the weak association between trades and logins (Figure 2) suggest that investors care directly about portfolio information above and beyond its role in trading. It is impossible, of course, to know what was in the mind of investors who logged in. However, while some logins are for trading purposes, a substantial part of financial attention does not lead to immediate trading but may instead be an adult version of "shaking the piggy bank."

Previous research has used trading as a proxy for investor attention (e.g., Barber and Odean 2008). Comparing the login and trading distributions, however, it is clear that, empirically, trading drastically underestimates investor attention relative to logins. Trading volume, as a proxy for attention, includes two measurement errors: First, trading is a combination of both attention and an additional active decision to change security holdings. Investors may, however, pay attention to their portfolio even when they do not trade. In our analysis, the active decision to trade after paying attention is called the "conditional trading" decision. Second, trading volume depends not just on how many investors are paying attention and trading, but also on how much they trade.

2. Returns and investor behavior

Figure 3 provides a first look at how investor attention and trading change with market conditions over time. It plots the daily total number of accounts with logins (jagged middle line), the total number of accounts with trades (lower line), and the level of the Dow Jones Industrial Average (upper line). Since we are interested in how investor attention responds to public information, our analysis uses the Dow because it is arguably the most widely disseminated and publicized stock index in the U.S. news media.[15]

Our sample period includes a wide range of market conditions. 2007 was a relatively quiet year during which the Dow rose on approximately 60% of days, with an average daily change of 0.03%. In contrast, 2008 was much more volatile due to the global financial crisis. In 2008 the Dow rose on only 47% of days, with an average daily change of -0.11%, and in September and October, the U.S. stock market had some of the largest price swings since the 1930s.

[15] Using the S&P 500 and NASDAQ indices gives similar results.

The number of account logins is volatile with both high frequency spikes and low frequency movement. At a daily frequency, there is a clear seasonality with lower attention over weekends.[16] Figure 3 also plots the daily smoothed means of logins using Symmetric Nearest Neighbor Smoothing. Under relatively calm conditions (as in 2007), changes in the number of logins are clearly positively correlated with changes in the index. However, during the financial crisis in late 2008, many investors logged in to check their accounts even though, given the extremely visible news media reporting about falling stock prices, they would have expected to see bad news. Note also that aggregate trading is only weakly correlated with the Dow, or with logins, for most of the two-year period. Daily spikes in trading do not line up with spikes in logins and vice versa. One notable exception is the market crash in the fall of 2008 which had high logins and trading. In general, however, the data are consistent with a large non-trading component in investor attention.

III. Aggregate attention and trading

In this section, we investigate patterns in aggregate attention and trading. We show that an aggregate ostrich effect is operative for returns over multiple horizons and is robust to allowing for return non-linearities. We also show how market volatility and media coverage affect attention. Our findings are strongly consistent with information-dependent utility but are difficult to reconcile with a purely trading-based explanation for attention. Further, we use the trading-attention identity in (1) to decompose patterns in trading into patterns in attention and conditional trading.

1. Aggregate attention

Investors may condition decisions to pay attention to their personal portfolio on a variety of public signals. This is both because investors may try to control the hedonic impact of financial information, as with the ostrich effect, and because the usefulness of information for trading may vary as described in Section I. In Table 3 Panel A, we estimate a number of different regression specifications for aggregate attention using (the logarithm of) the total daily number of investors who logged in to their account as the dependent variable. Only trading days are included in the sample. All

[16] Figure IA-3 in the Internet Appendix shows further login seasonality across the days of the week.

of our regressions (here and below) routinely include day-of-the-week dummy variables. Specification 1 is a "starting-point" regression controlling only for day-of-week effects. The regression R^2 shows that 7 percent of aggregate daily logins is explained by the day of the week.

Specification 2 regresses aggregate daily logins on day-of-the-week dummy variables and on a daily "down-Dow" dummy variable which equals 1 if the return on the Dow over the previous day was negative and 0 otherwise. The ostrich effect predicts a negative coefficient on the down-Dow dummy variable. The estimated down-Dow coefficient in Specification 2 indicates that the total daily number of logins drops by an estimated 9.5% following a daily market decline. Thus, investors are significantly less likely to log-in the day after a market decline, thus confirming the basic ostrich effect (Hypothesis H1). The explanatory power of this effect is sizeable, since the regression R^2 almost doubles to 0.13.

Attention may also be affected by market returns over longer time horizons. Specification 3 includes two additional return dummy variables defined based on whether the Dow fell over the balance of the previous week (i.e., excluding the prior day) and over the balance of the previous month (i.e., excluding the prior week). The results strongly support ostrich effects over each of these different return intervals (Hypothesis H1). Thus, the ostrich effect appears to induce path-dependence on the market index in investor attention.[17] The pattern of how the market rose or fell to its current index level affects how investors pay attention.

Investors may also condition their attention decisions on other public signals besides just lagged returns. Specification 3 also includes two additional signals. The first is the daily number of market-related front-page articles in the *New York Times* and *Wall Street Journal*, which we use as a proxy for news media attention.[18] The second signal is the VIX index, which we use as a proxy for investor expectations about future market volatility. The results show that logins are strongly increasing, as one might expect, in news media reporting on the stock market (Hypothesis H3). The

[17] The impact of the prior day's return appears large relative to the pro-rata impact of more distant past daily returns. This could be an attenuation effect in the emotional saliency of older information. In current work-in-progress, we are exploring the relation between this path dependence and the duration between individual investor logins.

[18] Data was coded for the NYT and WSJ front page articles with titles that contained the words, "stock" or "market" or "shares" or "Dow" or "Wall Street." Articles containing the word "market" but that were referring to unrelated markets, such as "job market" and "labor market," were excluded. Searchable text data for these two newspapers became available starting February 2007.

point estimate of the News Count coefficient means that logins increase by about 4% per additional front-page article on the stock market in the *Wall Street Journal* or the *New York Times*. Perhaps more interestingly, logins decrease when the VIX goes up and forward-looking investors expect more volatile future market conditions. The VIX coefficient indicates that a 10 unit increase in the VIX (e.g., from 20 to 30) leads to a 4% decrease in logins. This confirms a qualitative channel from volatility to attention consistent with the volatility ostrich effect (Hypothesis H2). In contrast, trading-motivated attention seems unlikely to decrease in market volatility. Importantly, the News Count and VIX do not overturn the basic ostrich effect result. Hence, the ostrich effect is not proxying for a pure media attention effect or volatility effect. The explanatory power of Specification 3 is substantial, raising the R^2 to 0.31.[19]

The last specification in Table 3 Panel A allows for a richer functional relationship between attention and prior index returns. Specification 4 includes down-Dow dummy variables for each of the three time interval and also allows positive and negative Dow returns to have possibly different linear impacts. The basic ostrich effect again predicts a negative coefficient on the down-Dow dummy variables. An extended version of the ostrich effect also predicts positive coefficients on the lagged returns, to the extent that larger positive (negative) returns induce even more (less) attention. The results for Specification 4 again confirm the existence of the basic ostrich effect based on the sign of returns (i.e., the coefficients on the down-Dow dummy variables are all negative and statistically significant) but indicate a non-linear relationship between attention and the magnitude of lagged returns. In particular, the negative coefficients on negative returns mean that the basic ostrich effect can be overwhelmed by a demand for information after large negative returns.[20] This demand for information in extreme down markets may result from investors assessing whether potentially to rebalance their portfolio. However, given the generally low level of actual trading, this may also

[19] Adding just the two longer down-Dow variables to Specification 2 increases the R^2 to 0.18, so the incremental R^2 from the VIX and News Count variables in Specification 3 is 0.13.

[20] Additional unreported regressions show that these non-linearities are robust after controlling for the number of investors trading (to verify that the increased attention in the late 2008 bear market was not simply a consequence of the late 2008 trading spike). We also verify that confirmed ostriches (described in Section IV.2) also exhibit increased attention after extreme negative Dow returns. Thus, non-ostriches alone are not driving the increased attention in extreme down-markets.

simply reflect non-trading curiosity. It should be remembered here that our sample period includes the dramatic stock market declines of the 2008 financial crisis.

Although the relationship between returns and logins is non-monotone, as a practical matter, the expected number of logins after a zero previous day return is greater than after negative returns up to returns of roughly -3% (which are empirically rare). The same is true for returns over the prior week, and the comparison is even stronger for the prior month where the critical negative return is -6%. The estimated coefficients for the News Count and VIX in Specification 4 are still statistically significant and have the same signs as in Specification 3. The combined explanatory power of the right-hand-side variables in this "super" regression leads to a R^2 of 0.38.

Gherzi et al. (2014) also find increased attention after both positive and negative large daily returns (which they call the meerkat effect). This leads them to dismiss the ostrich effect. However, we first note that some of their results for weekly returns are consistent with the ostrich effect. Thus, their evidence on the ostrich effect is actually mixed. Second and more importantly, our interpretation of the data differs from theirs and is based on a much larger sample. We argue that multiple factors are at play, one of which is the ostrich effect. Given that the ostrich effect holds both on average (given just the return sign) and conditionally (when returns are not too extreme), the evidence suggests that different behaviors are dominant over different ranges of returns.

The nonparametric Symmetric Nearest Neighbor Smoothing (SNNS) procedure gives a useful perspective on non-linearities over different return intervals without imposing a specific functional form. Figure 4 shows a scatterplot of the aggregate number of daily logins and lagged daily returns over the full two-year sample period. The figure also shows the smoothed means and the 95% confidence interval for the number of logins estimated excluding the most extreme positive and negative returns (> +/- 4%). A positive but non-linear relationship between returns and logins is clearly visible. If extreme daily returns are included in the SNNS estimation, then the smoothed means curve up for both positive and negative extreme returns. This is consistent with the non-monotone relationship in Specification 4 in Table 3 Panel A, which suggests a possible information-seeking curiosity (e.g., a meerkat effect) when returns are extreme. However, as can be seen in Figure 4, the increase in logins for large negative returns is due to a small number of extreme observations concentrated mainly in the market crisis in late 2008. This suggests again that investors may behave differently in extreme conditions. However, our non-parametric analysis also highlights the need for caution when interpreting regressions with non-linear return variables, since a small number of extreme outliers can be very influential. Thus, we view Specification 3 with down-Dow dummy variables as the most robust. However, Specification 4 allows for a parsimonious amount of return non-linearity.

2. Attention and trading

This section presents empirical results using the trading decomposition described in Section I. Panel B in Table 3 reports regressions of conditional trading, $\ln(NT_t) - \ln(NL_t)$, on the same sets of factors as in Panel A.[21] Panel C gives the corresponding regression results for observed total trading, $\ln(NT_t)$. We are interested here in attributing patterns in trading to underlying patterns in aggregate attention and in conditional trading since these two components of trading have different behavioral causes. We do this by comparing coefficients across the three sets of regression.[22] Our discussion focuses on Specification 3 (which, we argue above, is likely to be more robust) and Specification 4 (which includes parsimonious non-linearities).

We start by considering the two non-return factors. The News Count has a consistently positive significant relationship with both investor attention (Panel A) and conditional trading (Panel B). Thus, the strong positive relationship between observed trading and News Counts (Panel C) is due to both attention and conditional trading. However, the relationship between trading and volatility is more complex. The VIX is negatively related to logins in Panel A(the volatility ostrich effect), but positively related to conditional trading in Panel B (i.e., investors who login when volatility is high are more likely to trade). Hypothesis H4 says that differences like this across the

[21] We also ran the conditional trading regressions with $\ln(NT_t)$ as the dependent variable and with $\ln(NL_t)$ as an additional explanatory variable. The definition of conditional trading constrains the coefficient on $\ln(NL_t)$ to be 1. A coefficient different from 1 would mean that $\ln(NL_t)$ is correlated with omitted conditional trading factors. Table IA-1 in the Internet Appendix shows that $\ln(NL_t)$ is strongly significant in the unconstrained conditional trading regressions, and that the coefficients on $\ln(NL_t)$ are positive, statistically significant, and relatively close to 1. Including $\ln(NL_t)$ increases the unconstrained conditional trading regression R^2s by 0.14 or more relative to the trading regressions in Panel C.

[22] The sums of the coefficients on the different variables in Panels A and B are very close to the coefficients in Panel C in Table 3. This is by construction, since E[y+z| x] = E[y|x} + E[z|x]. Any differences are due to rounding and the fact that a small number of trades occurred via phone rather than logins.

two components of trading are possible given the different behavioral motivations. However, the net effect of volatility on observed trading in Panel C is ambiguous. In Specification 3, the relationship is positive and statistically significant (consistent with previous research) while, in Specification 4, it is negative but not statistically significant. Just looking at the observed trading regressions would mask the strong underlying offsetting behavioral complexity relating to volatility.

Next, we turn to the relationship between trading and lagged returns. Consider Specification 3 first. In this case, the negative comovement of attention with the down-Dow dummy variables in Panel A (the ostrich effect) is largely offset by positive comovement of conditional trading with the down-Dow dummy variables in Panel B. This result for conditional trading is inconsistent with overconfidence and realization utility bursts (which predict increased trading after positive market returns), but is consistent with bargain-hunting, doubling-down, and stop-loss strategies after large losses.[23] The net effect in Panel C is that observed trading is not significantly correlated with the down-Dow return metrics in our sample. However, our decomposition once again shows that there is more going on behaviorally below the surface—in attention and conditional trading—than the results for observed trading in Specification 3 might suggest by themselves (again, consistent with H4).

Next, consider the results for trading and returns using the more flexible Specification 4. Now none of the down-Dow dummy variables in Panel B are statistically significant for conditional trading, but the daily and weekly return coefficients are negative and mostly statistically significant. This is again consistent with conditional trading motivated by bargain-hunting, doubling-down, and stop-loss strategies after large negative returns. Observed trading reflects the combined effect of the return-driven patterns in conditional trading and in aggregate attention. The daily and weekly down-Dow dummy variables for observed trading in Panel C are negative and statistically significant (due to the ostrich effect in attention), but large negative returns cause trading to increase (due to both curiosity in attention and to conditional trading). However, the up-return coefficients are either not significant or (in one case) only marginally so. Evidence of non-linearities in trading is relatively new (e.g., see Ben-David and Hirschleifer 2012). Our results show that trading non-linearities arise from the interaction of the different behaviors driving attention and conditional trading (Hypothesis H4).

[23] Our data only indicate whether account-holders traded, but not what they bought or sold.

A few comments are in order concerning how our trading results relate to the prior trading literature. First, trading volume and lagged-returns are generally positively correlated in previous research, but Griffin et al. (2007) shows that the correlation is much weaker in down-markets in the U.S. Since our sample period includes one of the worst bear market in U.S. history, the absence of a significant association between observed trading and the down-Dow dummy variables in Specifications 2 and 3 and the non-monotone or negative relations in Specification 4 are, perhaps, not surprising in Panel C. Second, our sample consists of retirement accounts rather than general brokerage accounts that may involve more aggressive trading related to investor confidence. Third, our dependent variable is a measure of the *breadth* of trading (number of accounts with trades), but it excludes trade *size*, which is likely to be a significant driver of volume and which may also be related to investor confidence.

3. Do ostriches rest on the Sabbath?

If investors log in and check their accounts on Saturday and then log in again on Sunday, we hypothesize they are doing this more for psychological reasons rather than purely to get additional portfolio information (since prices have not changed) or to trade immediately (since markets are closed). A strong prediction of the ostrich effect is that the frequency of "double" weekend logins should be positively related to prior market returns. To test this prediction, we regress the total number of accounts in our 100,000 paperless sample that had logins on both Saturday and Sunday (during a given weekend) on the prior market returns. The sample comprises the 92 regular two-day weekends over these two years. Table 4 shows that the coefficients on the prior Friday return and the prior week return are both strongly positive.[24] This is consistent with the prediction that more investors pay attention to their portfolios when they can savor good news than when they expect to revisit bad news (a version of Hypothesis H1).

IV. Attention behavior of individual investors

[24] Column 2 shows that the explanatory power of the prior week (which includes the prior Friday) is not just due to the prior Friday.

The panel structure of our data let us investigate the cross-sectional attention behavior of individual investors. We show how attention is affected by investor demographics, life-stage, and personal financial circumstances. We also decompose demographic patterns in trading into patterns in attention and trading for individual investors. Lastly, we link ostrich behavior with investor risk-bearing and also strengthen our results on the link between attention and trading by linking these variables for individual investors.

1. Attention and investor characteristics

We have already noted the substantial heterogeneity in attention across investors in Figure 1 and Table 2. In this section, we explore how investor attention is related to investor characteristics. Table 5 Columns 1 through 5 report the results from OLS regressions for the daily login decisions of individual investors using the panel of 100,000 investors for the full 2007-2008 sample period. The total number of observations is over 40 million. The dependent variable in these regressions is an indicator variable equal to 1 if investor *i* logged in to check their account on day *t*; and equal to 0 otherwise. All of the regressions include dummy variables for the day of the week. We estimate panel regressions using OLS and compute standard errors allowing for clustered (correlated) errors within accounts and over time (see Cameron, Gelbach and Miller 2001).

As a starting point, Specification 1 regresses individual daily login decisions on the down-Dow dummy variable for the previous day. The coefficient on the down-Dow dummy variable is negative and statistically significant, which supports the ostrich effect (H1). The low R^2 for individual investor login decisions is not surprising given the extreme heterogeneity in daily login decisions in Table 2. However, the large R^2 for the aggregate login regression in Table 3 shows that this small amount of explanatory power for individual investors becomes substantial when aggregated across the entire pool of investors.

We then extend this regression by identifying differences in attention for specific types of investors. Specification 2 adds demographic and monthly account information controls.[25] The results show that females log in less often than males, that investors with a college education are less

[25] The Internet Appendix reports univariate results for logins which are similar to multivariate results here.

likely to log in, and that logins are U-shaped in age. The relationship with age may reflect lifecycle changes in the perceived importance of retirement savings. Middle-aged investors may be busy with family and other obligations whereas older investors may be more concerned about their imminent retirement (consistent with Hypothesis H5). The high rate of logins by younger investors may reflect cohort effects of how younger investors use online applications.

Turning to the monthly account variables, Specification 2 shows that investors with larger account balances are more likely to log in. This is consistent with larger dollar investment performance having greater emotional salience (Hypothesis H5). Logins are not correlated with the portfolio mix of equity and bonds in this particular regression but they are correlated in later specifications controlling for more sources of cross-sectional login variation. Specification 2 also includes investors' own realized account returns over the prior month as an explanatory variable. At first glance, the causal interpretation of this variable may seem unclear since investors cannot know the return on their own account until they log in. However, given knowledge of their personal portfolio composition, investors can form expectations of their personal returns using more public information than simply the Dow. Thus, the realized own account return should be interpreted here as an explanatory variable (expected account return given all available public information) measured with error (the realized return surprise). The positive relationship between the own monthly account return and login decisions is another expression of ostrich effect behavior. However, the ostrich effect with respect to the Dow still continues to be significant even when the monthly realized own return is included in the regression.

We also identify investor and account characteristics associated with different levels of ostrich behavior. Specification 3 includes multiplicative interactions between various demographic variables and the down-Dow dummy variable. However, since there is no evidence that the ostrich effect depends non-linearly on age or interacts with education, we focus on Specification 4, which is the same as Specification 3 except that the statistically insignificant ostrich interactions with age-squared and college are omitted. Including the linear age interaction causes the baseline down-Dow coefficient to switch sign and become positive, but this does not contradict the ostrich effect. Since the average age in the sample is 45, the net effect of the down-Dow dummy adjusted for age is still negative for all but the very youngest investors.[26] The negative coefficient on the age interaction means that older investors are empirically more prone to ostrich behavior. This is consistent with Hypothesis H5 and greater emotional saliency of retirement account returns with older age. Females are less prone than males to exhibit ostrich behavior. Investors with large account balances are also more prone to ostrich behavior given the negative sign the account size interaction term (consistent with Hypothesis H5). The ostrich effect is decreasing in the fraction of bonds in investors' portfolios (Hypothesis H7). Although ostrich behavior and equity risk-taking are positively correlated, the direction of causality is not identified. Ostrich behavior may encourage investors to take more risk (by taking larger stock positions), or the risk from larger stock positions may lead to ostrich behavior as a coping mechanism. Intuitively, we expect weaker ostrich behavior in investors holding mostly bonds since stock returns are more informative about the performance of equity portfolios than bond portfolios. (We revisit this finding in Section IV.3 below.) Specification 5 confirms that high media coverage and low volatility also continue to increase attention (Hypotheses H2 and H3).[27]

Next, we estimate the attention/conditional trading decomposition but now using panel data. This lets us attribute demographic patterns in trading to separate demographic patterns in attention and conditional trading. In terms of trading, Specification 7 in Table 5 shows results from a panel regression using the same explanatory variables as in Specification 5, but now with a dependent variable equal to a 0/1 trading dummy variable indicating whether investor i traded (rather than logged in) on day t. The coefficients in the trading regression represent the combined effect of attention and conditional trading. In the Internet Appendix, we show that the conditional trading component can be isolated by re-estimating this same trading regression but restricted to a subsample of days on which investors actually logged in.[28] The conditional trading results are in Specification 6. Comparing the last three columns in the table shows how demographic patterns in attention

[26] For a 45-year old investor the age-adjusted impact of the prior daily down-Dow is [0.0108 – 0.0007 x 45] = -0.0207. For a 65-year old investor, this age-adjusted negative effect is even larger at -0.0347.

[27] We also estimated Specification 5 using logit as a robustness check. However, the logit standard errors are only clustered on accounts, not time. The results for the marginal effects in the logit model are similar to those from OLS.

[28] The complication in estimating conditional trading with panel data is that we cannot use the log specification since the login and trading dummy variables can be zero for some days and investors.

(column 5) together with patterns in conditional trading (column 6) combine to produce demographic patterns in trading (column 7).

Our analysis reveals a variety of novel demographic patterns (Hypothesis H6). For example, the well-known fact that women trade less than men (Barber and Odean 2001) is due to gender differences in both attention and conditional trading. Women are less likely to pay attention to their account then men and, conditional on paying attention, less likely to trade. In contrast, the U-shaped pattern in attention given age is more than offset by an inverted U-shaped pattern in conditional trading given age, so that total trading has a net inverted U-shaped pattern given age. We also see that gender differences in the ostrich effect are offset by opposing gender differences in conditional trading so that, on balance, there is not a statistically significant gender difference in the propensity to trade in down markets.

Table 6 further explores the panel properties of attention given the fact that some account characteristics vary over time. Here we estimate fixed-effect panel regressions which control for unobserved investor and time-invariant account characteristics. Almost all of the login results in Table 5 continue to hold under the fixed-effect specification. Since the fixed-effect estimation is driven by within-investor variation around the mean, we can strengthen the causal interpretations of our findings. For example, the statement that "investors with larger balances are more likely to login" can be strengthened to "investors are more likely to log in when their account balance gets larger." In addition, after controlling for investor fixed-effects, investors become significantly less likely to log in and their ostrich behavior weakens when the percentage of bonds in the account increases (again supporting Hypothesis H6). Moreover, controlling for investor fixed effects shows that at least some causality goes from equity holdings to ostrich behavior. Specification 4 shows again that logins are still increasing in media coverage and decreasing in the VIX. As a final summary test, Specification 5 shows that the ostrich effect also continues to hold for returns over the prior week and month in this fixed effect specification.

These differences in attention across investors provide insights into the role of psychology and emotion in investing. The investment usefulness of portfolio information is arguably similar for stockholders and bondholders, but the stock market rising is *emotionally* bad news for bondholders, and so bondholders pay less attention in rising stock markets. Similarly, investors with large portfolios arguably would benefit from financial information equally in rising and falling markets, but they tend to pay less attention when it is emotionally painful.

2. Prevalence of ostrich behavior

Our panel regression results confirm an overall ostrich effect, but they also show variation in ostricity across investors. We explore individual variation further by estimating the benchmark regression (with the daily down-Dow dummy variable) separately for each investor account. Table 7 reports on sorts of accounts based on their estimated down-Dow coefficients. The left panel reports on the full sample of all 100,000 paperless accounts. The estimated down-Dow coefficient is negative for 53.8% of the sample (consistent with ostrich behavior) and positive for 43.4% of the sample; with 2.7% of the sample having no logins over 2007-2008. In the right panel we restrict the breakdown to accounts for which the estimated return coefficient is significantly different from zero at the 5 percent level (i.e., where $|t| > 2$). Given the low number of logins for many accounts, ostrich classification can be imprecise for these accounts. Within the sub-sample for which the estimated return/login relationship is statistically significant, about 79% of these investors are confirmed ostriches, while only 21% are confirmed "anti" ostriches.

We conjecture that an investor's predisposition towards ostrich behavior is a stable personality trait over time. We test this hypothesis by investigating whether investors who display ostrich behavior in 2007 also display ostrich behavior in 2008. For each individual investor we estimate two separate regressions using our benchmark specification (with the daily down-Dow dummy); one for calendar year 2007 and one for 2008. Thus, for each investor we have two estimated coefficients, β_{07} and β_{08}, measuring their ostricity in each of the two sample years. If ostrich behavior is a stable personality trait over time, then the β_{07} and β_{08} coefficients should be positively correlated across individuals.

Figure 5a shows a positive visual association for the full sample of all 100,000 paperless accounts. The simple Pearson correlation between β_{07} and β_{08} is 0.393, and the Spearman rank correlation is 0.173. Figure 5b shows that the positive association is even stronger for investors for whom both β_{07} and β_{08} are significantly different from zero. The large cluster of negative β_{07} and β_{08} estimates in the lower left are stable confirmed ostriches, the small cluster in the upper right are stable confirmed anti-ostriches, and the two small off-diagonal clusters are unstable confirmed “switchers.” Including only accounts where both β_{07} and β_{08} are significantly different from zero, the simple correlation is 0.4589, and the Spearman rank correlation is 0.3673. This intertemporal stability supports the hypothesis that ostricity is a persistent personal trait.[29]

We also are interested in the robustness of ostrich behavior in individual investors over different return horizons. To assess this, we ran three separate univariate regressions for each investor to estimate down-Dow coefficients corresponding to returns over the prior day, week and, month. The Pearson correlations between the daily, weekly and monthly down Dow coefficients are all high (ranging from 0.61 to 0.79) as are the Spearman rank correlations (ranging from 0.47 and 0.65). The high correlations of the ostrich metrics for the different return windows increase our confidence in the robustness of our investor classifications. The logins of individual investors seem to react similarly to market returns over different horizons.

3. Zero equity holdings

The ostrich effect prediction of a positive relationship between logins and lagged index returns should not apply to individuals with no equity in their accounts. For zero-equity investors, stock market returns will be much less informative about the value of their personal portfolios, and, thus, we would not predict ostrich behavior (Hypothesis H7). Therefore, a sample of accounts with zero equity can serve as a strong test of the ostrich effect.

To test this prediction, we examine the estimated down-Dow coefficients from benchmark regressions estimated separately for each investor for all accounts that never held equity over the full 2007-2008 period. Since this is a small subset of investors, we expand our sample, in this one instance, beyond the 100,000 paperless accounts to include all zero-equity accounts in the full sample of 1.2 million accounts. There are 66,468 accounts with zero equity. Table 8 shows that the percentage of zero-equity investors who are anti-ostriches is significantly greater than the percent of ostriches. Comparing investors with only significant down-Dow coefficients, the ratio of confirmed ostriches to anti-ostriches flips from 79/21 =3.76 in the 100,000 paperless sample (see Table 7) to 33/67 = 0.49 when we only include accounts with zero equity.

[29] Estimating the partial correlation between the two coefficients and controlling for the average portfolio mix of stocks and bonds over the two-year period does not alter our results. Persistence in some of the investor characteristics investigated in Section IV.1 may help explain some part of the persistence of ostrich behavior, but the persistence in Figures 5a and 5b is not limited to the effect of just these identified characteristics.

The theoretical model in Karlsson et al. (2009) predicts that investors with zero-equity should not behave as ostriches, but it does not predict anti-ostrich behavior. However, this anti-ostrich behavior could arise for several possible reasons. One explanation is that zero-equity investors are actually behaving as ostriches with respect to the bond market to the extent that stock and bond returns are negatively correlated (e.g., Treasury bond prices rose in the 2008 crash). Another possible explanation is that the zero-equity investors are behaving like ostriches with respect to some kind of comparative information. For example, bondholders may be comparing themselves to stockholders, in which case a rising stock market is bad news and a falling stock market is good news. In other words, bondholders may interpret good and bad news in terms of relative "keeping up the Joneses" comparisons with other investors whose portfolios, on average, contain stock. Alternatively, the comparisons may be relative to a mental accounting equity benchmark (given the widespread pro-equity retirement advice) or, if they recently sold their stock, to what they would have earned if they had kept the stock. Relative comparisons such as these turn positive (negative) stock returns into bad (good) news for zero-equity investors.

4. Ostrich behavior and trading

Attention matters, in part, because it is likely to be related to other investor behaviors. In Tables 5 and 6, we saw that ostrich behavior and equity risk-taking are connected. In this section, we extend our results in Table 5 that ostricity and trading are related now to the level of individual investors. We do this by cross-tabulating a measure of an investor's propensity to trade in down markets with their ostricity. The first step is to subdivide our sample of 100,000 paperless accounts into six subsamples based on the individual login regressions described in Table 7: Confirmed ostriches (investors for whom the t-statistic on their down-Dow coefficient is less than -2), moderate ostriches (with down-Dow t-statistics between -1 and -2), moderate anti-ostriches (with down-Dow t-statistics between 1 and 2), confirmed anti-ostriches (with down-Dow t-statistics more than 2), investors who cannot be classified as ostriches or anti-ostriches (with down-Dow t-statistics between -1 and 1), and investors who never logged in. The subset of investors of indeterminate status includes ostriches and anti-ostriches who simply did not log in enough to be identified as such and also individuals whose login decisions are truly unaffected by prior market index returns.

We conjecture that ostriches trade less in down markets since they pay less attention in down markets. To test this prediction, we estimate a second individual regression for each account in which the dependent variable is now a *trade* indicator variable (equal to 1 on days on which the investor traded and 0 otherwise) and where the explanatory variable is again the daily down-Dow dummy (along with the standard day-of-the-week control variables). The down-Dow coefficient in this second regression measures an investor's predisposition to trade in down markets. This analysis is related to our attention-trading decompositions, but here differences in ostrich behavior and trading propensities are considered without conditioning on specific demographic characteristics.

Table 9 cross-tabulates the distribution of down-Dow coefficients from the individual investor trading regressions for each of the ostrich-status subsamples.[30] We find a monotone cross-sectional relationship between investor ostricity and their down-market trading propensities (Hypothesis H8). Confirmed anti-ostriches and moderate anti-ostriches, and investors who cannot be classified all trade more in down-markets than in up-markets, whereas moderate ostriches split their trading between up and down markets, and confirmed ostriches trade more in up-markets than in down-markets. When we compute the cross-sectional correlation between investor login and trading coefficients, we find it is positive and significant at the 99 percent level.

V. Conclusion

This paper is the first large-scale investigation of *how often* and *when* investors pay attention to their personal portfolios and of how attention affect trading. Our main findings are:

- Attention is, on average, higher after positive returns than after negative returns. However, curiosity and increased monitoring for potential trading opportunities can cause investors to log in and pay attention despite predictable bad news after extreme negative returns.
- A volatility ostrich effect means that logins are decreasing with the VIX. Attention is also increasing in news media reporting on the stock market.

[30] In a handful of cases, investors did not log-in to trade but rather submitted trades via phone calls.

- Patterns in aggregate trading can be decomposed into separate patterns in attention and conditional trading. Attention and conditional trading both cause trading to be increasing in news media stock market coverage, but they have opposing effects on the relationship between trading and market volatility. They also induce non-linearities in the relationship between trading and lagged returns. Similarly, demographic patterns in trading can be decomposed into separate demographic patterns in attention and conditional trading.
- The average level of attention and ostrich behavior varies with investor demographics. Men, older investors, and wealthier investors are more likely to pay attention to their portfolios and to behave as ostriches. Ostrich behavior also appears to be a stable personality trait.
- Ostrich behavior and equity risk-bearing are positively related. In addition, investors displaying ostrich behavior are less likely to trade following market downturns.

We argue that these patterns in attention, and the high level of attention relative to trading, are consistent with a hedonic impact of attention on information utility. More generally, our research contributes to a larger literature on the economics of attention. One novel feature of our study is that attention is a dependent variable rather than an explanatory variable. In this respect, our paper is a field-study counterpart to research employing process-tracing techniques to investigate information acquisition by decision-makers (Gabaix et al 2006; Payne, Bettman and Johnson 1988) and players of economic games (Camerer et al. 1993, Costa-Gomes and Crawford 2006, Crawford 2008).

There are many fruitful directions for future research on investor attention. One set of issues concerns how attention affects financial performance and portfolio holdings. Empirically, ostriches hold larger equity positions, but it may be possible to identify the direction of causation using natural experiments (e.g., changes in online information or experimental manipulation). It would also be interesting to track the investment performance of ostriches and non-ostriches.

Another set of promising research issues is suggested by the substantial heterogeneity in attention behavior across individuals and over time. For example, the ostrich effect should be more pronounced among investors who discount the future more steeply. Attention in down-markets imposes an immediate hedonic cost due to the bad news, but an expected future gain for loss-averse investors from resetting their loss-aversion wealth reference point. In addition, direct measures of investor confidence (e.g., from surveys) may be correlated with investor attention. The relationship between consumption risk aversion and information risk aversion is also of interest. For example, bond-holders may differ from equity-holders because of a dislike for both psychological informational risks as well as actual financial risks. Dynamic portfolio allocation and security selection decisions may also affect attention. There may also be differences in attention between pension and regular brokerage accounts. The effect of changing technology (e.g., automated web-based interfaces) on attention and on the investment advisory process is another natural research issue.

A further set of questions concerns linkages between attention, investor sentiment, pricing, and liquidity. Our two-year sample is too short to test the asset pricing effects of attention, but this would be possible with a longer sample. In particular, the relationship between attention and the volatility risk premium could be investigated. In addition, cross-sectional differences in the portfolio holdings of ostriches and other types of investors may also affect pricing, trading, and liquidity for individual stocks and industry sectors. The relationship between news media financial coverage and attention is another topic of interest. Finally, attention may also play a role in episodes of investor exuberance (Shiller 2000), since trading requires, first and foremost, attention.

In closing, the idea of attention as a cognitive pathway both to process information and to experience utility, together with the availability of data on online investor behavior, has the potential to lead to a richer understand of financial markets and household behavior.

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Table 1
Descriptive Statistics
Mean/Median and (Standard Deviation)
Full sample and 100,000 paperless accounts, 2007-2008

Variable	Paperless	Full Sample
Age (years)	45.80/45.57	46.33/46.46
	(10.44)	(10.44)
% Female	31.6	36.9
Tenure with Employer (years)	12.45/10	13.13/10
	(8.92)	(9.32)
% Equity in account	77.12/86	73.39/83
	(26.83)	(29.14)
Account Balance (dollars)	118,90/59,925	102,973/50,224
	(187,663)	(173,815)
Wealth (dollars)	420,570/90,816	336,675/60,540
	(1,161,023)	(1,021,342)

Table 2
Distribution of Days Logged-In and Days Traded
100,000 paperless accounts, 2007-2008

Percentile	Logins	Trades
1%	0	0
5%	1	0
10%	4	0
25%	11	0
50%	36	1
75%	115	2
90%	242	5
95%	338	8
99%	507	21
Mean	85.2	2.03
Std. Dev.	113.32	5.19
Skewness	2.08	11.59

Table 3
Aggregate Logins, Conditional Trading, and Trading
OLS regression results, 100,000 paperless accounts, 2007-2008

	Panel A: log of Logins				Panel B: log of Trades-log of Logins				Panel C: log of Trades			
	1	2	3	4	1	2	3	4	1	2	3	4
(Dow return on previous trading day) * UP				2.471***				-4.305***				-1.834
				(0.818)				(1.353)				(1.700)
(Dow return on previous trading day) * DOWN				-1.846**				-5.403***				-7.249***
				(0.935)				(1.650)				(2.047)
(Dow return over 4 days prior to last trading day) * UP				-0.353				-1.872*				-2.225*
				(0.474)				(0.985)				(1.150)
(Dow return over 4 days prior to last trading day) * DOWN				-2.161***				-3.617***				-5.779***
				(0.582)				(1.007)				(1.249)
(Dow return over 15 days prior to last 5 trading days) * UP				0.192				-0.960				-0.768
				(0.459)				(0.877)				(1.018)
(Dow return over 15 days prior to last 5 trading days) * DOWN				-1.251***				-0.654				-1.904***
				(0.248)				(0.522)				(0.584)
Down Dow dummy for previous trading day		-0.095***	-0.079***	-0.058***		0.124***	0.075***	-0.023		0.029	-0.004	-0.082**
		(0.015)	(0.014)	(0.016)		(0.030)	(0.025)	(0.032)		(0.033)	(0.030)	(0.038)
Down Dow dummy for 4 days prior to last trading day			-0.041***	-0.083***			0.058**	-0.025			0.017	-0.108***
			(0.014)	(0.019)			(0.026)	(0.032)			(0.030)	(0.038)
Down Dow dummy for 15 days prior to last 5 trading days			-0.043***	-0.077***			0.054**	0.020			0.012	-0.056
			(0.014)	(0.020)			(0.027)	(0.040)			(0.031)	(0.046)
News Counts			0.039***	0.032***			0.054***	0.038**			0.093***	0.070***
			(0.008)	(0.007)			(0.016)	(0.016)			(0.019)	(0.018)
Most recent prior closing VIX			-0.004***	-0.008***			0.008***	0.006***			0.004***	-0.003
			(0.001)	(0.001)			(0.001)	(0.002)			(0.001)	(0.002)
Constant	9.908***	9.952***	10.060***	10.122***	-3.214***	-3.270***	-3.582***	-3.426***	6.694***	6.681***	6.478***	6.695***
	(0.015)	(0.018)	(0.023)	(0.026)	(0.023)	(0.025)	(0.043)	(0.051)	(0.029)	(0.032)	(0.053)	(0.058)
Day-of-week dummy variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.13	0.31	0.38	0.30	0.32	0.49	0.52	.20	0.20	0.30	0.37
N	502	502	484	484	502	502	484	484	502	502	484	484

* Standard errors in parentheses

* p<.10, ** p<.05, *** p<.01

Table 4
Prior Market Returns and the (log of) Number of Investors who Logged-in on both Saturdays and Sundays
OLS regression results, 100,000 paperless accounts, 2007-2008

	1	2	3
Dow return on Friday	2.863**	1.876	
	(1.122)	(1.146)	
Dow return over the prior week		1.235***	1.479***
		(0.462)	(0.441)
Constant	8.008***	8.011***	8.011***
	(0.017)	(0.016)	(0.017)
Adjusted R^2	0.06	0.12	0.10
N	92	92	92

* Standard Errors in parentheses
*p<.10, **p<.05, ***p<.01

Table 5

Investor Logins, Trading Conditional on a Login, Trading, Investors' Characteristics, and Market Conditions

OLS panel regressions results, 100,000 paperless Accounts, , 2007-2008

	Login					Conditional Trading	Unconditional Trading
	1	2	3	4	5	6	7
Down Dow dummy	-0.017***	-0.016***	0.008	0.011***	0.013***	0.00005	-0.0002
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.0005)	(0.0002)
If Female		-0.045***	-0.050***	-0.050***	-0.050***	-0.003***	-0.001***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.0004)	(0.00008)
Age on 12/31/08		-0.008***	-0.008***	-0.008***	-0.008***	0.001***	0.0002***
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0001)	(0.00003)
Age^2		0.0001***	0.0001***	0.0001***	0.0001***	-0.00001***	-0.000002***
		(0.000006)	(0.000007)	(0.000006)	(0.000006)	(0.000002)	(0.000000)
College		-0.010***	-0.010***	-0.010***	-0.010***	-0.0005	-0.0002***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.00008)
Account Balance (10,000)		0.0009***	0.001***	0.001***	0.001***	0.00008***	0.00005***
		(0.00005)	(0.00006)	(0.00006)	(0.00006)	(0.00001)	(0.000004)
Percent Bonds		0.0009	-0.013***	-0.013***	-0.008**	0.0198***	0.005***
		(0.003)	(0.004)	(0.004)	(0.004)	(0.001)	(0.0004)
AccountMonthly Return		0.122***	0.121***	0.122***	0.063***	-0.0196***	-0.009***
		(0.025)	(0.025)	(0.025)	(0.023)	(0.006)	(0.003)
(Dow-down)*Female			0.010***	0.010***	0.010***	-0.001***	-0.0001
			(0.001)	(0.001)	(0.001)	(0.0004)	(0.0002)
(Dow-down)*Age			-0.0006**	-0.0007***	-0.0007***	0.00002	0.000003
			(0.0003)	(0.00007)	(0.00007)	(0.00001)	(0.000005)
(Dow-down)*Age^2			-0.000001				
			(0.000003)				
(Dow-down)*College			0.0002				
			(0.0004)				
(Dow-down)*account Balance			-0.0002***	-0.0002***	-0.0002***	0.00002**	0.000003
			(0.00003)	(0.00003)	(0.00003)	(0.000007)	(0.000003)
(Dow-down)*(Percent Bonds)			0.029***	0.029***	0.0312***	0.004*	0.002**
			(0.004)	(0.004)	(0.005)	(0.002)	(0.0008)
News Counts (NYT &WSJ)					0.006***	0.001***	0.0004***
					(0.001)	(0.0003)	(0.0001)
VIX					-0.0007***	0.00005*	0.00001
					(0.00008)	(0.00003)	(0.000008)
Constant	0.154***	0.190***	0.180***	0.178***	0.239***	-0.0008	0.005*
	(0.003)	(0.029)	(0.029)	(0.029)	(0.027)	(0.006)	(0.003)
Day of week Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.01	0.02	0.02	0.02	0.02	0.01	0.005
N	44,418,050	40,323,260	40,323,260	40,323,260	38,388,356	6,129,832	38,388,356

Standard errors in parentheses are clustered within accounts and by date

* p<.10, ** p<.05, *** p<.01

Table 6
Logins, Investors Characteristics, and Market Conditions
OLS panel regressions with fixed effects, 100,000 paperless accounts, 2007-2008

	1	2	3	4	5
DOW down dummy for prior day	-0.017***	-0.016***	-0.015***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Account Balance (10,000)		0.002***	0.002***	0.001***	0.001***
		(0.0002)	(0.0002)	(0.0001)	(0.0001)
Account Monthly Return		0.107***	0.107***	0.064***	0.029
		-0.025	(0.025)	(0.023)	(0.022)
Percent Bonds		-0.0301***	-0.041***	-0.029***	-0.028***
		(0.0040)	(0.004)	(0.004)	(0.004)
(Dow-down)*account Balance			-0.0004***	-0.0004***	-0.0004***
			(0.0000)	(0.0000)	(0.0000)
(Dow-down)*(Percent Bonds)			0.022***	0.023***	0.023***
			(0.003)	(0.003)	(0.003)
News Counts (NYT &WSJ)				0.006***	0.007***
				(0.001)	(0.001)
VIX				-0.0006***	-0.0006***
				(0.0001)	(0.0001)
Down Dow dummy for 4 days prior to last trading day					-0.008***
					(0.002)
Down Dow dummy for 15 days prior to last 5 trading days					-0.007***
					(0.002)
Constant	0.154***	0.029	0.030	0.078***	0.117***
	(0.003)	(0.025)	(0.025)	(0.023)	(0.023)
Day of week Dummy	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.01	0.01	0.02	0.02	0.02
N	44,418,050	44,418,050	44,418,050	42,286,658	42,286,658

Standard errors in parentheses are clustered by date
* p<.10, ** p<.05, *** p<.01

Table 7
Ostrich Classification of Investors
Based on Estimated DOWN Coefficients in Individual Investor Regressions
Daily account data for 100,000 paperless accounts, 2007-2008

	Full Sample		Only Significant Coefficients	
Ostrich	Freq.	Percent	Freq.	Percent
No (β >0)	43,426	43.43	2,900	20.92
Yes (β<0)	53,841	53.84	10,962	79.08
No logins	2,733	2.73	n.a.	n.a.
Total	100,000	100	13,862	100

Table 8
Ostrich Classification of Investors with Zero-Equity Accounts
Daily data for all zero-equity accounts out of 1+ million Vanguard accounts, 2007-2008

	Full Sample		Only Significant Coefficients	
Ostrich	Freq.	Percent	Freq.	Percent
No (β>0)	22,122	33.28	1,148	67.25
Yes (β<0)	16,915	25.45	559	32.75
No logins	27,431	41.27	n.a	n.a.
Total	66,468	100	1,707	100

Table 9
Distribution of Investors by their Level of Ostrichness and Their Tendency to Trade
Conditional on Prior Daily Market Trend (Up or Down)
Daily account data for 100,000 paperless accounts, 2007-2008

	Significant (|t|>2)		Moderate (1<|t|<2)				
	Trade Down	Trade Up	Trade Down	Trade Up	Never traded	The rest	Total
Ostrich	88	117	1,371	1,282	3,619	4,485	10,962
Moderately-Ostrich	86	61	1,725	1,318	7,124	4,954	15,268
Moderately-Anti-Ostrich	135	20	2,241	513	7,173	3,494	13,576
Anti-Ostrich	42	5	667	96	1,281	809	2,900
Never logged	1	2	73	21	2,463	173	2,733
The rest	390	148	7,611	3,351	27,172	15,889	54,561
Total	742	353	13,688	6,581	48,832	29,804	100,000

Figure 1

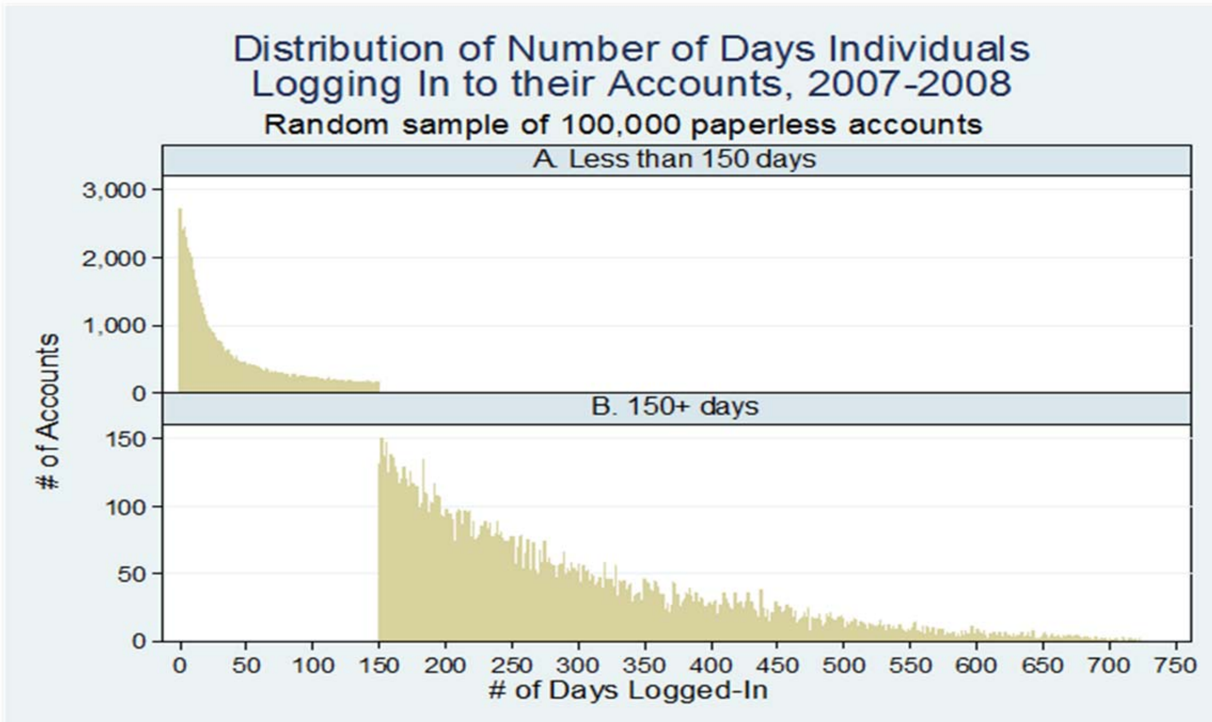


Figure 2

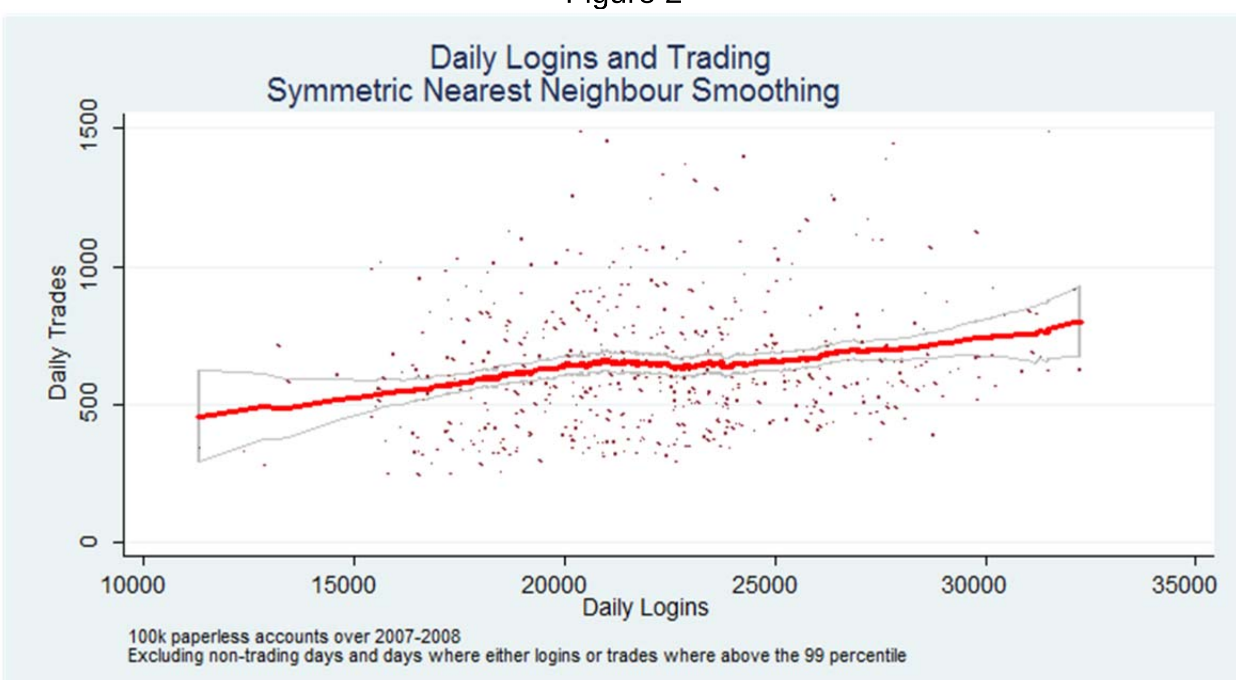


Figure 3

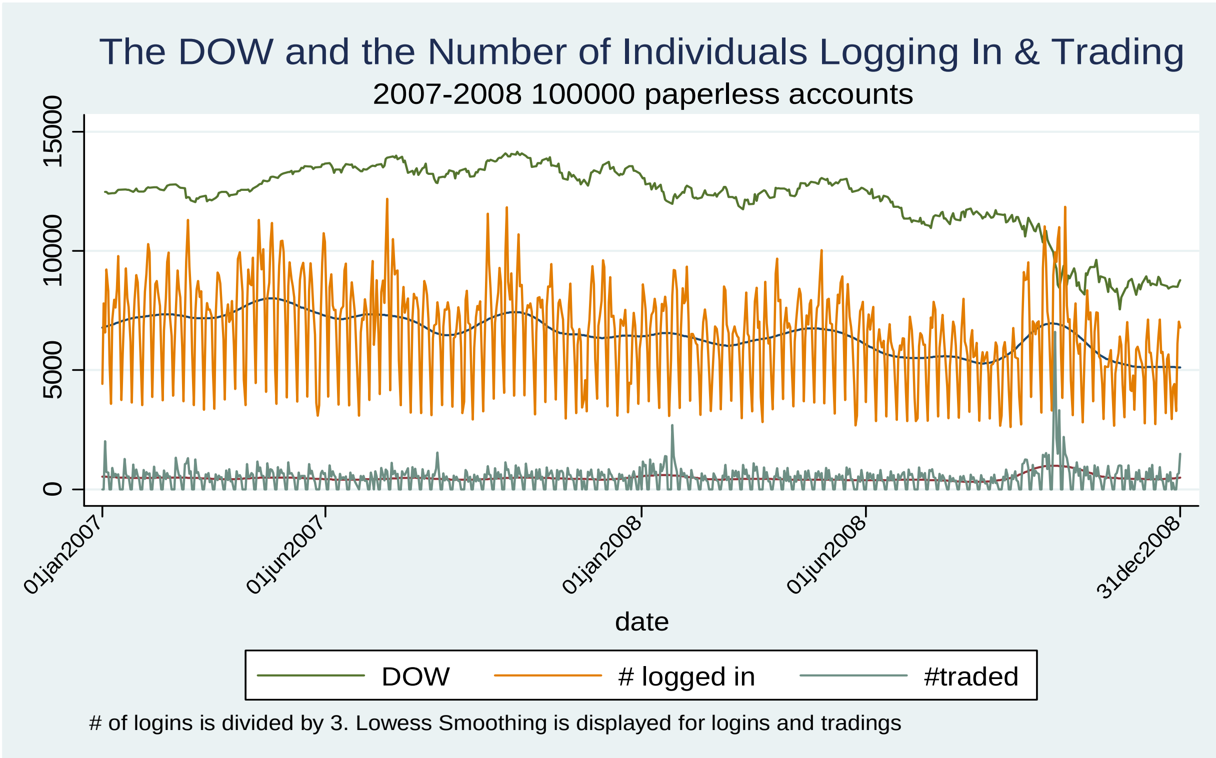


Figure 4

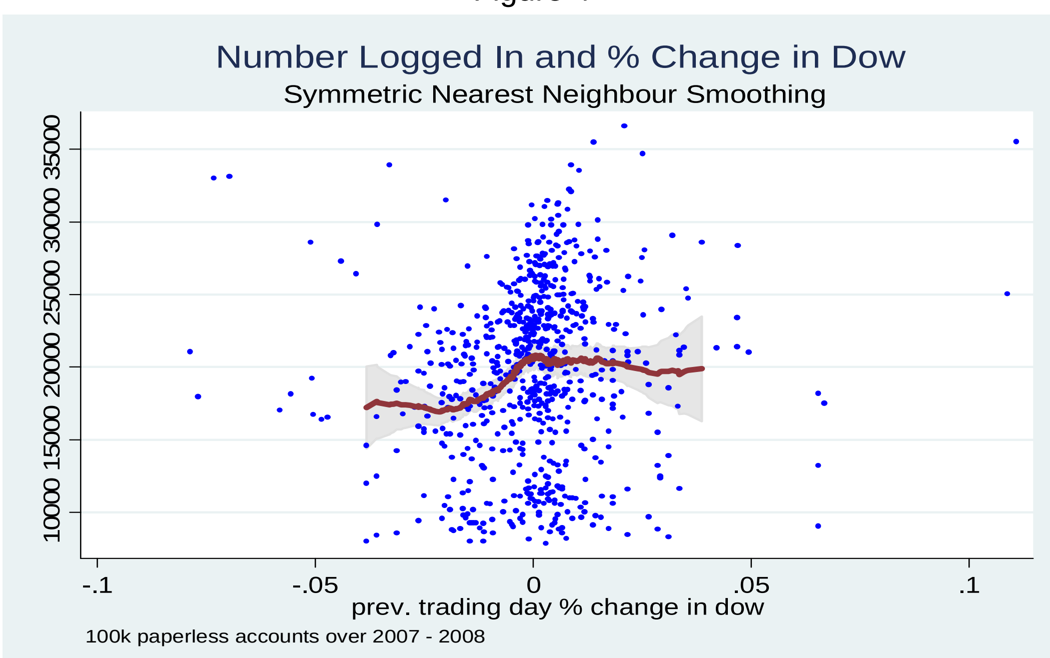


Figure 5(a)

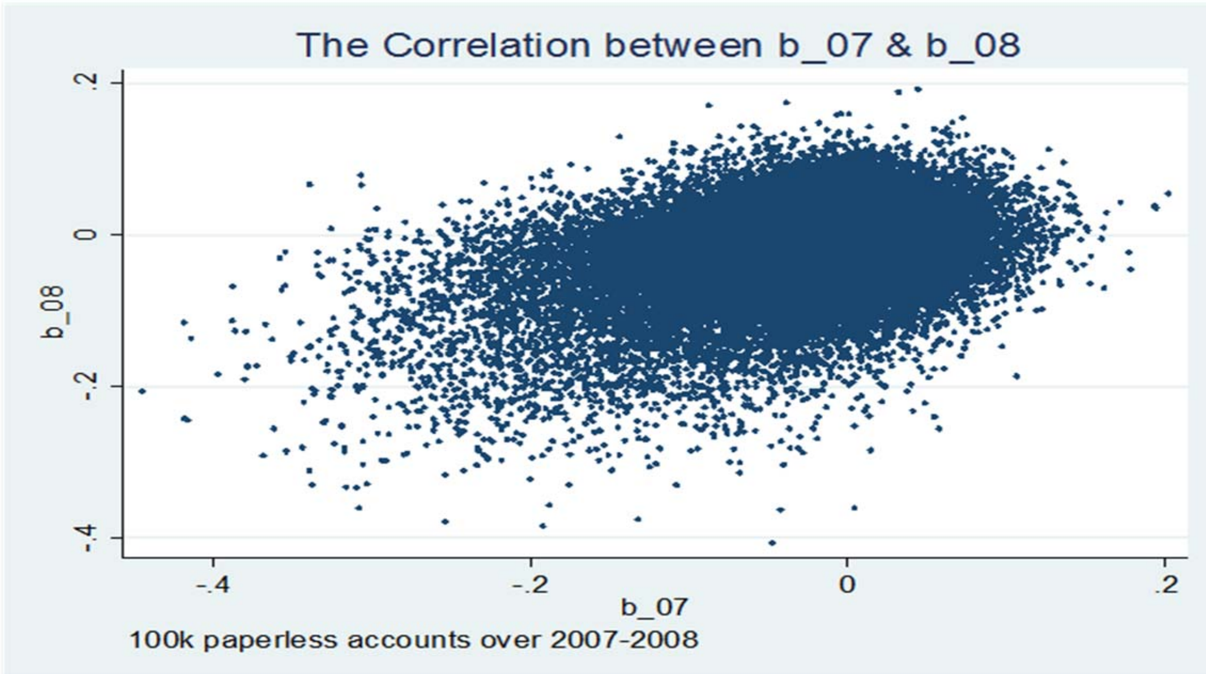
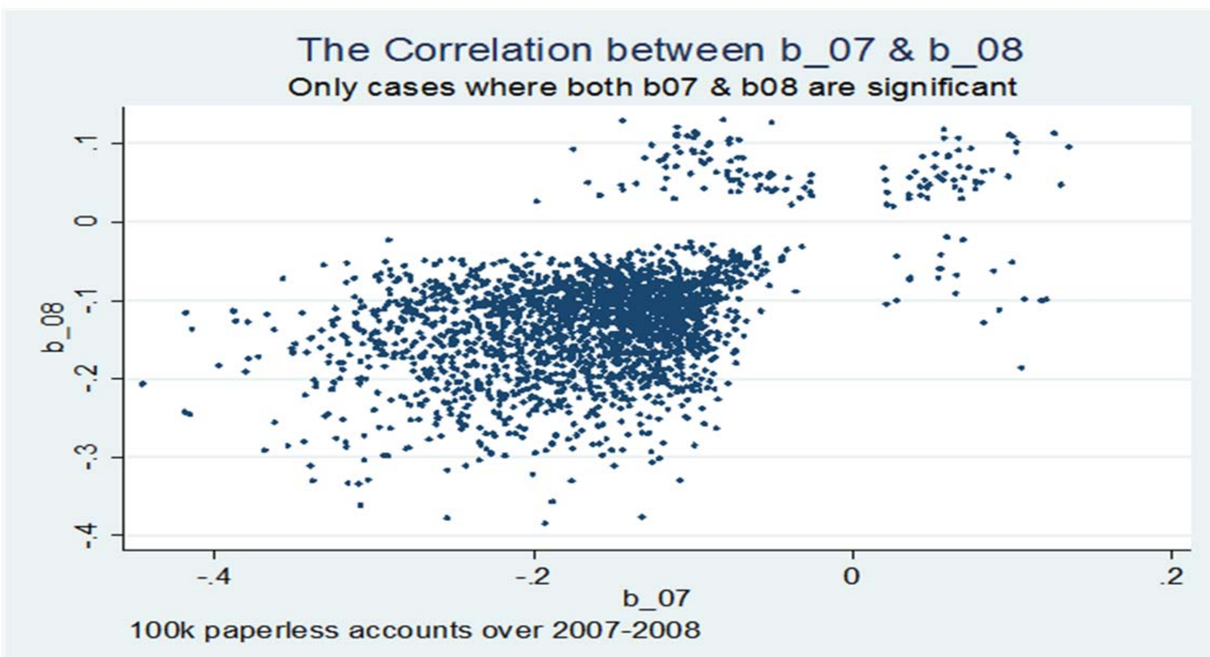


Figure 5(b)



Internet Appendix

1. Investor characteristics and behavior.

The life-situation of investors is likely to influence their attention to their finances. Tables 5 and 6 in the paper investigate these issues in a multivariate regression analysis. This appendix reports univariate evidence. The univariate results are qualitatively similar to the multivariate results.

Figures IA-1a and IA-1b show scatterplots of the relationship across accounts between investor age (on Dec. 31, 2008) and the total number of days with logins per account and the total number of days with trading per account. The considerable heterogeneity in account logins (and, thus, investor attention) is readily apparent from the cloud of dots corresponding to the individual accounts. For visual clarity, the plots stop at 200 days logged-in and 15 days with trading. The solid lines in the figures show the fitted means conditional on age estimated using Symmetric Nearest Neighbor Smoothing. The data in the estimation are trimmed to exclude extreme outliers in the top 1 percent of days logged in (more than 506 days) and days with trading (more than 20 days). The 95% confidence intervals around the fitted means are very tight except for trading at ages above 70 (where the data are sparse and the confidence interval bands widen visibly). Between ages 20 and 40 the mean number of days with logins declines by roughly 30 days and then increases to around age 60 by about 30 days. At older ages the trend in logins seems flatter. In contrast, trading is much more stable in investor age, increasing slightly until around age 60 followed by a slight decline thereafter.

Figures AI-2a and IA-2b are scatterplots of the relationship between dollar account balances on Dec. 31, 2008 and the number of days with logins and trading. Again using Symmetric Nearest Neighbor Smoothing, the smoothed mean number of days with logins increases strongly with the account balance up to around $500,000 and then increases more weakly up to around $1.5 million, after which (not shown) there are relatively few observations (less than 1 percent of the sample) and no clear trend. Trading is also increasing with account balance, especially at low balance levels, but again, given the relatively small number of trades, the data are relatively noisy. Certainly, on an absolute scale, the changes in trading with account balances are smaller than those for attention.

Prior research (Barber and Odean 2001) has found significant gender differences in trading. These differences are also present in our retirement account sample. The average number of days with trading for accounts of female investors is 1.41, while the average number trading days for accounts of male investors is 2.30. We also find gender differences in attention. Female investors logged into their accounts 64.73 days on average while male investors logged in 94.80 days, which is roughly 50% more frequent than females.

The regression analysis in the paper routinely includes day-of-the-week dummy variables. Figures IA-3 shows the average number of logins across weekdays and over weekends.

2. Robustness of conditional trading estimation

Table IA-1 reports results from reestimating the conditional trading regressions with $\ln(NT_t)$ as the dependent variable and with $\ln(NL_t)$ as an additional explanatory variable. The definition of conditional trading constrains the coefficient on $\ln(NL_t)$ to be 1 (see Footnote 20 in the paper). A coefficient estimate different from 1 in the unconstrained regression means that $\ln(NL_t)$ is correlated with omitted conditional trading factors. We see here that the estimated coefficients on $\ln(NL_t)$ in the unconstrained conditional trading regressions are positive, statistically significant, and relatively close to 1.

3. Attention/trading decomposition using panel data

This section describes how to estimate the attention/conditional trading decomposition using panel data. Let $T_{i,t}$ denote a dummy variable equal to 1 if investor i traded on day t and 0 otherwise, and let $L_{i,t}$ denote an analogous dummy variable for logins by investor i on day t. We then define the conditional trading variable C_{it} for investor i on day t in terms of the identity $T_{i,t} = L_{i,t}\, C_{it}$. Column 5 in Table 5 estimates a linear model for daily investor login decisions of the form $L_{i,t} = bX_{i,t} + e_{i,t}$ where $X_{i,t}$ is a set of explanatory variables for investor i on day t. Column 7 estimates a linear model for daily investor trading decisions $T_{i,t} = aX_{i,t} + u_{i,t}$.

If a linear model $C_{it} = gX_{i,t} + \varepsilon_{i,t}$ generates conditional trading, then, using the definition, $T_{i,t} = L_{i,t}\, C_{it}$, we have

$$T_{i,t} = L_{i,t}\,(gX_{i,t} + \varepsilon_{i,t}) \rightarrow T_{i,t} = g\, L_{i,t}\, X_{i,t} + L_{i,t}\, \varepsilon_{i,t}$$

Since both the explanatory variables $L_{i,t}\, X_{i,t}$ and the error term $L_{i,t}\, \varepsilon_{i,t}$ are multiplied by $L_{i,t}$, we can estimate the conditional trading model $C_{it} = gX_{i,t} + \varepsilon_{i,t}$ using $T_{i,t}$ as the dependent variable and restricting the sample to days on which investors actually logged in (i.e., where $L_{i,t} = 1$). Results from the conditional trading regression are in Column 6 of Table 5.

4. Additional information regarding trading-attention cross-sorts

Section IV.4 in the paper investigates the relation between the ostrich effect and trading. This analysis is based on cross-sorts of regression coefficients measuring investors' ostricity and their predisposition to trade in down-markets. Here we report addition background information on this analysis. Table IA-2(a) reports the average number of days with logins and the average number of days with trading for each ostrich-status subgroup. Confirmed ostriches and anti-ostriches log in relatively frequently, but this is, at least in part, due to the fact that the statistical power to detect systematic ostrich or anti-ostrich behavior is increasing in the number of logins when the fraction of days on which an investor logged-in is low. However, confirmed ostriches also *trade* more frequently than the other types of investors. Table IA-2(b) reports analogous results for our measure of investor propensity to trade in down markets.

Internet Appendix Table 1

Aggregated (log) Number of Trades

OLS regression results, 100,000 paperless accounts, 2007-2008

	1	2	3	4
log (number of logins)	0.858***	0.947***	1.270***	1.237***
	(0.093)	(0.102)	(0.097)	(0.099)
(Dow return on previous trading day) * UP				-4.890***
				(1.368)
(Dow return on previous trading day) * DOWN				-4.966***
				(1.621)
(Dow return over 4 days prior to last trading day) * UP				-1.788*
				(0.969)
(Dow return over 4 days prior to last trading day) * DOWN				-3.105***
				(1.068)
(Dow return over 15 days prior to last 5 trading days) * UP				-1.005
				(0.877)
(Dow return over 15 days prior to last 5 trading days) * DOWN				-0.357
				(0.501)
Down Dow dummy for previous trading day		0.119***	0.097***	-0.010
		(0.034)	(0.028)	(0.033)
Down Dow dummy for 4 days prior to last trading day			0.069**	-0.005
			(0.027)	(0.035)
Down Dow dummy for 15 days prior to last 5 trading days			0.066**	0.039
			(0.028)	(0.040)
News Counts			0.044***	0.031**
			(0.014)	(0.014)
Most recent prior closing VIX			0.009***	0.008***
			(0.001)	(0.002)
Constant	-1.802*	-2.746***	-6.298***	-5.825***
	(0.920)	(1.018)	(0.996)	(1.018)
Day-of-week dummy variable	Yes	Yes	Yes	Yes
R^2	0.35	0.37	0.54	0.57
Adjusted R^2	0.34	0.36	0.53	0.56
N	502	502	484	484

* Standard errors in parentheses

* $p<.10$, ** $p<.05$, *** $p<.01$

Internet Appendix 2A
Mean Number of Days with Logins & Days with Trading
Sorted by Investor Ostrich Tendencies
Daily account data for 100,000 paperless accounts, 2007-2008

Investor Type	Days Logged	Days Traded
Ostrich	179.6	3.6
Anti-Ostrich	89.0	2.0
Moderately-Ostrich	103.1	2.2
Moderately-Anti-Ostrich	59.3	1.7
The Rest	71.7	1.8
Total	85.2	2.0

Internet Appendix 2B
Mean Number of Days with Logins & Days with Trading
Sorted by Investor Tendency to Trade on Up or Down Days
Daily account data for 100,000 paperless accounts, 2007-2008

	Days Logged	Days Traded
Trade Down	155.0	10.7
Trade Up	183.5	12.1
Moderately-Trade Down	99.6	3.0
Moderatey-Trade Up	123.5	4.0
The Rest	115.5	4.1
Total	85.2	2.0

Figure IA-1(a)

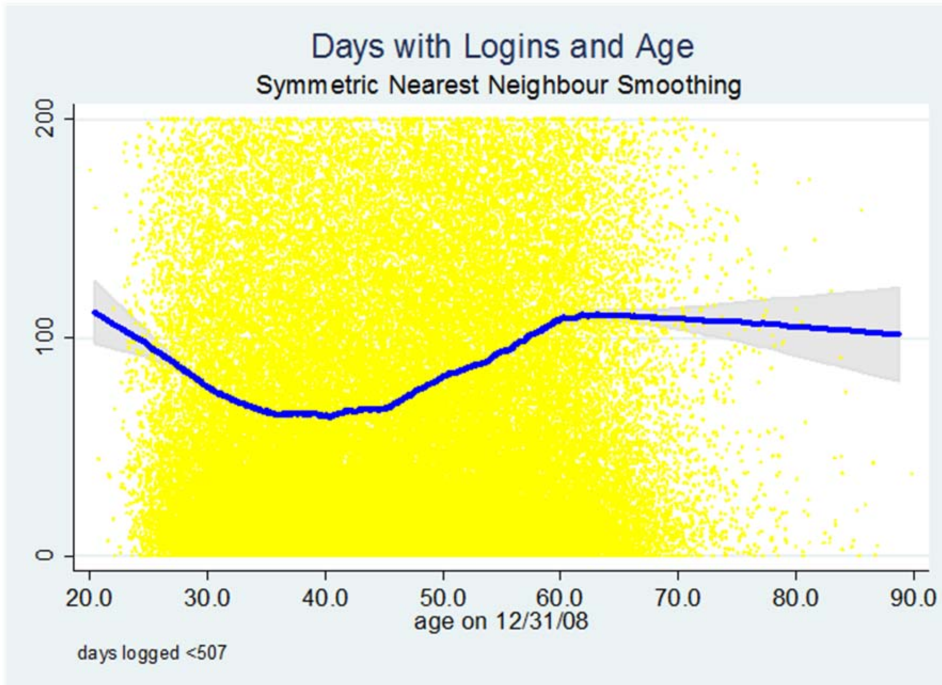


Figure IA-1(b)

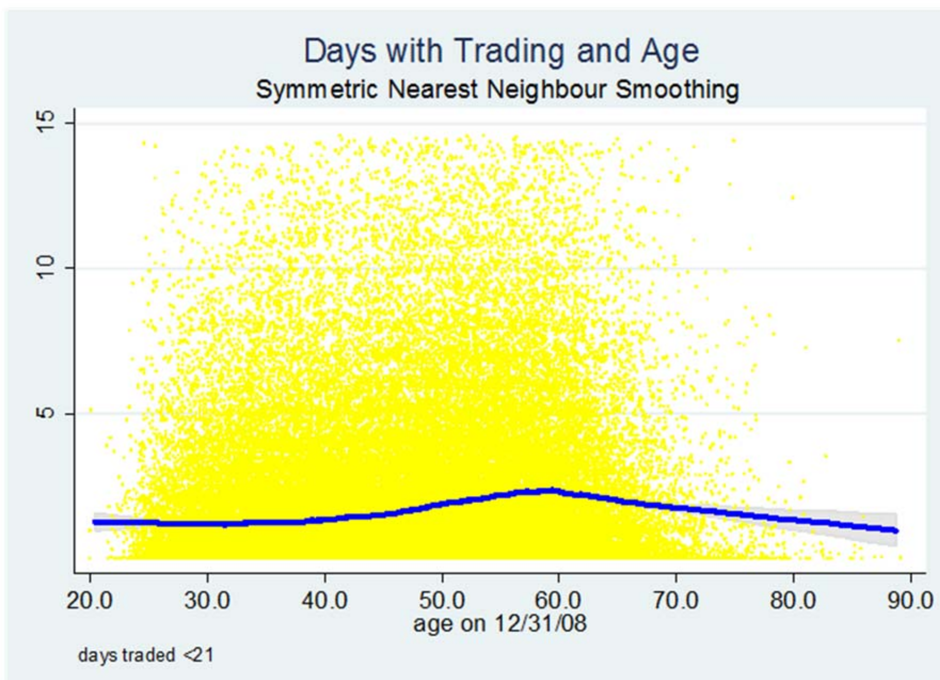


Figure IA-2(a)

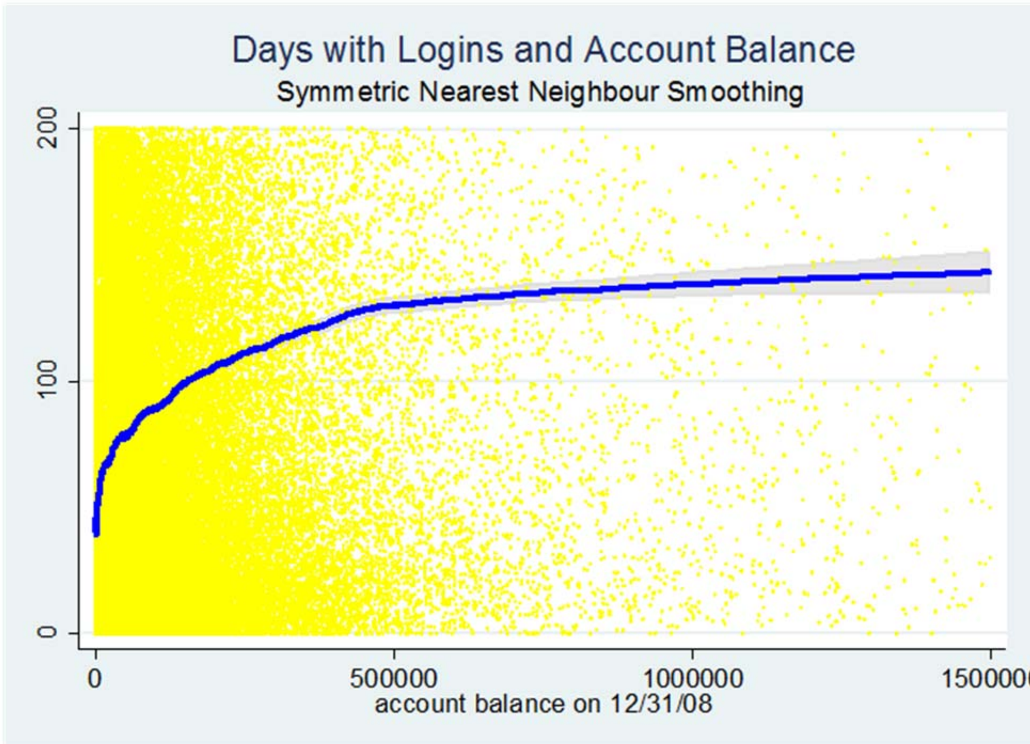


Figure IA-2(b)

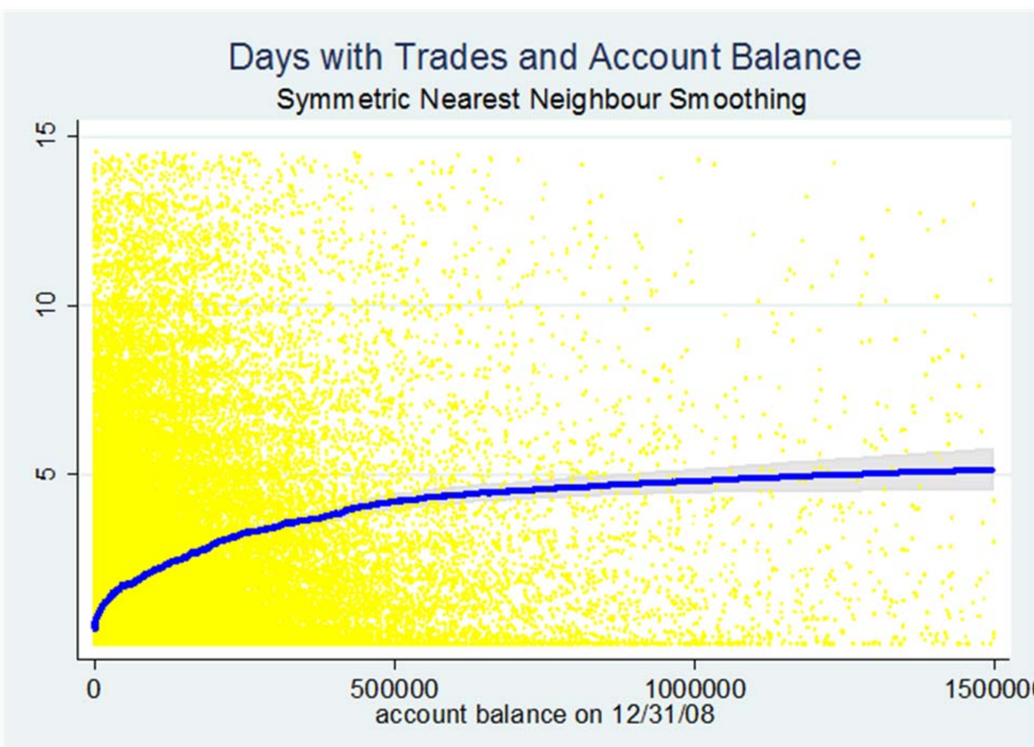
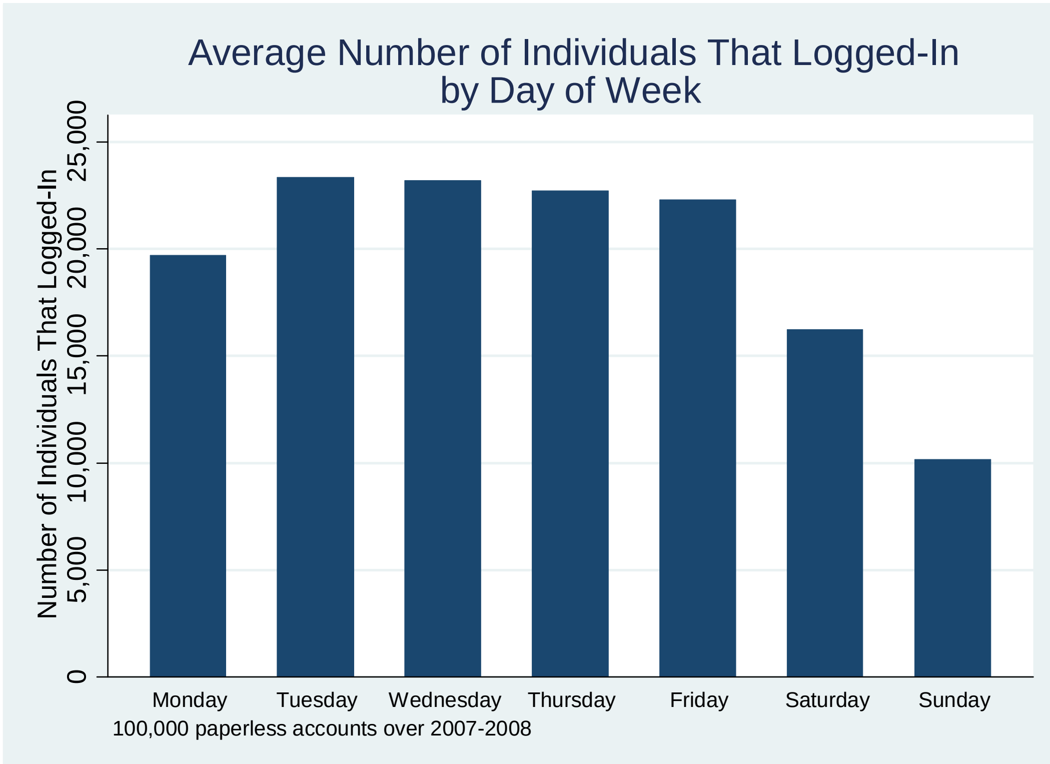


Figure IA-3


Average Number of Individuals That Logged-In
by Day of Week
Number of Individuals That Logged-In
0
5,000
10,000
15,000
20,000
25,000
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
100,000 paperless accounts over 2007-2008