A Generalization of the Calendar Time Portfolio Approach and the Performance of Private Investors*

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Abstract

We present a new, regression-based methodology for decomposing the risk-adjusted performance of private investors, firms, and mutual funds. Our technique allows for the inclusion of multivariate and continuous subject characteristics in the analysis and it ensures that the statistical results are robust to cross-sectional and temporal dependence. Considering a unique dataset on 40,000 European private investors, we apply our methodology to reassess some of the most popular hypotheses on the performance of private investors. By testing the various hypotheses on a stand-alone basis, we are able to confirm the results of previous studies. However, when we apply our methodological framework to perform a joint test of the hypotheses, our results question several findings from previous research on private investor performance. More generally, our results indicate that (1) testing for a specific hypothesis separately and (2) erroneously ignoring cross-sectional dependence in microeconometric data can both lead to severely biased statistical results.

Keywords: Performance measurement, Robust statistical inference, Fama-French model
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I. Introduction

The calendar time portfolio approach, or Jensen alpha approach, is a popular technique for analyzing the risk-adjusted performance of private investors, firms, or mutual funds by aid of a two-step procedure.[1] In the first step, period-by-period average excess returns for a group of individual subjects such as male or female investors are computed. The second step then regresses these period-by-period averages on a set of market factors (e.g., the three Fama-French factors). The intercept term of this time-series regression is then interpreted as the risk-adjusted performance of the subject group.[2]

Since the seminal work of Jaffe (1974) and Mandelker (1974), the calendar time portfolio approach (subsequently abbreviated as *CalTime* approach) has been applied in many different areas of empirical finance, such as for example in research on the performance of private investors (e.g., Barber and Odean, 2000, 2001, 2002; Seasholes and Zhu, 2005, 2007; Ivkovic, Sialm, and Weisbenner, 2008; Kumar and Lee, 2006), in studies on the long-run performance of stocks (e.g., Brav and Gompers, 1997; Fama, 1998; Mitchell and Stafford, 2000), in research on insider trading (e.g., Jaffe, 1974; Jeng, Metrick, and Zeckhauser, 2003), and in studies analyzing the performance of mutual funds and hedge funds (Kacperczyk, Sialm, and Zheng, 2008; Fung, Hsieh, Naik, and Ramadorai, 2008). A major advantage and reason for the popularity of the *CalTime* approach is its ability to allow for robust statistical inference when cross-sectional dependence is present. By aggregating the returns of an entire cross-section into a single portfolio, the problem of cross-sectional dependence amongst the individual subjects' returns is eliminated (Lyon, Barber, and Tsai, 1999).

Unfortunately, however, the *CalTime* approach's statistical robustness comes at a cost:

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[1] For simplicity, we will henceforth refer to investors only when discussing applications of the different approaches to investigate risk-adjusted performance. However, our insights can be applied to any research that relies on microeconometric panel data.

[2] See Kothari and Warner (2008) for a detailed discussion of the calendar time portfolio approach.

The *CalTime* approach is limited to the analysis of a single, binary investor characteristic. Although it is sometimes possible to naturally segregate investors into clear-cut groups such as men and women (e.g., Barber and Odean, 2001), some research questions necessitate the analysis of continuous or multivariate investor characteristics. For example, analyzing the impact of portfolio turnover on the performance of private investors (e.g., Barber and Odean, 2000) based on the *CalTime* approach turns out to be tricky as it is impossible to include the individual investors' portfolio turnover in the time-series regression of the second step. Researchers often circumvent this limitation of the *CalTime* approach by first segregating investors into sub-groups, such as deciles or quintiles, and then measuring the performance for each of these sub-groups independently based on the *CalTime* approach. However, such portfolio-sorts have a number of drawbacks. First, due to the lack of a natural grouping criterion, the resulting group definitions and eventually the results are somewhat arbitrary. Second, an analysis based on portfolio sorts has to be limited to just a few investor characteristics in order for the number of sub-groups not becoming too numerous. Third, it is difficult to comprehensively assess the statistical results of an analysis based on portfolio sorts and, as a consequence, statistical inference is often exclusively based on a comparison of the top and bottom sub-groups for simplicity.

In this paper, we present a new method for decomposing the risk-adjusted performance (or "alpha") of multifactor models. Our approach relies on estimating a pooled linear regression with cross-sectional correlation consistent Driscoll and Kraay (1998) standard errors. The model specification is such that the individual investors' monthly excess returns are regressed on the market factors (e.g., the three Fama-French factors), a set of individual investor characteristics, and all interaction terms between the market factors and the investor characteristics. We show both theoretically and empirically, that our regression-based technique is capable to perfectly replicate the results of the traditional *CalTime* approach in a single step rather than in two. Consequently, our method has the same statistical properties as the traditional *CalTime* approach. More importantly, however, our technique extends the traditional *CalTime* approach by allowing for the inclusion of continuous and multivariate investor characteristics in the analysis. This allows for a much richer decomposition of the risk-adjusted returns of private investors and makes it simple and straightforward to control for alternative investor characteristics and competing hypotheses. To our best knowledge, our methodology therefore resolves a major problem not yet addressed in prior research on long-term performance evaluation (see Kothari and Warner (2008) for a recent discussion) or panel data estimation procedures such as those surveyed in Petersen (2009).[3]

While Fama (1998) and Mitchell and Stafford (2000) strongly advocate the *CalTime* approach, this technique is far from being econometrically unobjectionable. Most prominently, Loughran and Ritter (2000) criticize that analyzing an unbalanced panel with the *CalTime* approach underweights observations from periods with large cross-sections and overweights observations from periods with small cross-sections. Specifically, they argue that "tests that weight firms equally should have more power than tests that weight each time period equally" (Loughran and Ritter, 2000, p. 363). By estimating a linear regression model, our approach naturally resolves the critique of Loughran and Ritter (2000) as it is straightforward to estimate our regression-based model with OLS where all observations are equally weighted.

Since the traditional *CalTime* approach is incapable to deal with continuous and multivar-

[3] In particular, note that the Fama and MacBeth (1973) approach, which is mainly covered and strongly advocated by Petersen (2009), is limited to the analysis of (excess) returns and does not allow for a decomposition of the *risk-adjusted performance*. After all, it is impossible to estimate cross-sectional regressions with variables that are constant across the cross-section. Risk factors like the market excess return (which are required for estimating the risk-adjusted performance) do not vary across firms or investors. Therefore, they cannot be included in the Fama-MacBeth procedure. Moreover, Vogelsang (2009) points out that the Fama-MacBeth estimator is inconsistent if there are individual fixed effects which are correlated with the regressors. In contrast, the *CalTime* approach is robust to this type of endogeneity since its coefficient estimates are completely invariant to the investor specific fixed-effects.

iate investor characteristics, Dahlquist, Engström, and Söderlind (2000), Ivkovich and Weisbenner (2005), and Korniotis and Kumar (2009) among others started to investigate the risk-adjusted performance of mutual funds and private investors by aid of cross-sectional regressions on the investor or fund level. Like the traditional *CalTime* approach, this alternative technique (which we refer to as the *CrossReg* methodology) constitutes a two-step procedure. However, compared to the *CalTime* approach, the ordering of the two steps that are inherent in the analysis is reversed. Correspondingly, the first step of the *CrossReg* procedure involves estimating a Fama and French (1993) type multifactor model for each single investor. The second step then decomposes the risk-adjusted performance of the investors by regressing the Fama-French alphas from the first step on a set of investor specific explanatory variables. In this paper, we show that the coefficient estimates from the *CrossReg* approach coincide with those of the regression-based technique we propose in this research. However, this is not the case for the standard errors because it is impossible to estimate cross-sectional dependence consistent standard errors for a regression model of a single cross-section (Driscoll and Kraay, 1998). As a result, the second-step regression of the *CrossReg* approach will always be based on the (implicit) assumption that the returns of the individual investors are cross-sectionally uncorrelated.

Although this presumption might look innocuous for a random sample of private investors, it is not. Cross-sectional dependence in the portfolio returns of private investors is likely to arise for at least two reasons. Besides the fact that social norms, herd behavior, and neighborhood effects can lead to contemporaneously correlated actions of the investors (Feng and Seasholes, 2004; Kumar and Lee, 2006; Dorn, Huberman, and Sengmueller, 2008), there is also a technical reason why stock returns of private investors are likely to be spatially dependent. Specifically, Seasholes and Zhu (2005, p. 4) argue that "over a single time period the return to any household's portfolio is simply a linear combination of the underlying assets' returns. The number of independent household returns is thus limited by the number of assets and not the number of households." Because of the potential consequences of erroneously ignoring cross-sectional dependence, the *CrossReg* approach is at risk of producing severely biased statistical results (Driscoll and Kraay, 1998).

In summary, our GCT approach combines the best of the *CalTime* and *CrossReg* methodologies: We can both control for investor characteristics *and* competing hypotheses *and* we can eliminate the problem of cross-sectional dependence in returns. In the second, empirical part of the paper, we apply our methodology to reassess some of the most popular hypotheses on the performance of private investors. We use a unique and previously unused dataset with account-level data on more than 40,000 private investors from a respectable European wholesale bank over the time period from March 2000 to June 2005. When testing a set of univariate hypotheses on the performance of private investors with our sample data, we can confirm most of the key results in Barber and Odean (2000, 2001, 2002), Ivkovic, Sialm, and Weisbenner (2008), and Seasholes and Zhu (2005). Specifically, we find that while the portfolio turnover is unrelated to the gross performance of private investors, it negatively impacts on their net performance (Barber and Odean, 2000). Moreover, male investors in our dataset underperform women (Barber and Odean, 2001) and online investors do worse than phone-based investors (Barber and Odean, 2002). In addition, we find that both the gross and net performance of the investors is negatively related to the number of stocks in their portfolio (Ivkovic, Sialm, and Weisbenner, 2008).

In line with Ivkovic and Weisbenner (2005) and Massa and Simonov (2006) our univariate analysis also indicates that Swiss residents' investments in Swiss stocks outperform those of non-Swiss residents. However, consistent with Seasholes and Zhu (2005), this result only holds when the cross-sectional dependence amongst the sample investors' returns is ignored.[4] Specifically, we find that (erroneously) ignoring cross-sectional dependence in the sample investors' returns can result in t-values that are three and more times higher than their cross-sectional dependence consistent counterparts. Most importantly, when we use our regression-based technique to test all hypotheses jointly *and* account for cross-sectional dependence, we find only the result that online investors underperform phone-based investors to remain significant whereas all the other univariate results are rendered insignificant.

The remainder of this paper is structured as follows. Section II formalizes our methodology. In Section III we describe our investor sample. Section IV empirically illustrates our regression-based extension of the calendar time portfolio approach. Furthermore, it validates some of the most popular hypotheses on the performance of private investors. Section V concludes.

II. Methodology

In the first part of this section we revisit the calendar time portfolio methodology (or the Jensen-alpha approach) which has originally been introduced by Jaffe (1974) and Mandelker (1974). We then present our panel regression based approach, to which we henceforth refer to as the "Generalized Calendar Time" (or GCT) regression model. We show that the GCT-regression model yields as a special case identical coefficient estimates and standard errors as the *CalTime* approach. Next, we show that our GCT-regression model can also be used to replicate the coefficient estimates of the *CrossReg* approach. However, the standard errors

[4] Note that since our methodological approach relies on estimating a linear regression model, it can also be estimated with standard errors that do not account for cross-sectional dependence (e.g. OLS standard errors). However, the standard variant of our methodology relies on estimating the regression model with Driscoll-Kraay standard errors which are robust to cross-sectional and temporal dependence.

and t-stats of the *CrossReg* methodology can not be adjusted such that they are robust to cross-sectional dependence in the data. Consequently, in this section, we show that our GCT-regression model combines the advantages of both the *CalTime* and *CrossReg* approaches: The standard errors are robust to cross-sectional correlation in the data and the model allows for the inclusion of continuous and multivariate investor-characteristics in the analysis.

A. The calendar time portfolio approach

In the first step of the *CalTime* methodology one constructs for each investor group a time-series of the group's mean excess return. This is achieved by averaging the month t excess returns y_{ht} of all N_{jt} investors h who belong to group j as[5]

$$y_{jt} = \frac{1}{N_{jt}} \sum_{h=1}^{N_t} z_{ht}^{(j)} y_{ht} , \qquad (1)$$

where $z_{ht}^{(j)}$ is a dummy variable which is equal to one if investor h belongs to investor group j and zero otherwise and $N_t = \sum_j N_{jt}$. The second step of the most recent variants of the *CalTime* methodology then measures the performance of the investor groups by aid of a linear k -factor regression model with y_{jt} from (1) as the dependent variable:

$$y_{jt} = \beta_{j0} + \beta_{j1} x_{1t} + ... + \beta_{jk} x_{kt} + \varepsilon_{jt} . \qquad (2)$$

In most applications, equation (2) is specified as a Jensen (1968), Fama and French (1993), or Carhart (1997) type regression. Therefore, the coefficient estimate for the intercept term ($\hat{\beta}_{j0}$)

[5] The term "investor group" should not be taken too literally. For instance, instead of forming investor group portfolios one could also construct portfolios of firms or portfolios that are based on certain asset holdings (see, e.g., Seasholes and Zhu, 2007). Furthermore, note that the *CalTime* methodology is by no means restricted to a first step aggregation of individual excess returns. In fact, any variable y_{ht} which varies over both t and h , respectively, may be aggregated in the first step of the procedure.

is typically of prime interest for judging whether or not investor group j performs well.

The use of the *CalTime* methodology is by no means limited to an analysis of the investment performance of single investor groups. It is straightforward to compare the performance of two investor groups. For instance, if a researcher wants to investigate whether or not women ($j = w$) have superior investment skills compared to men ($j = m$), she may do so by constructing a zero investment portfolio which is long in the women's portfolio and short in the portfolio of the men. Thus, in this case the dependent variable of the second step regression is given by $\Delta y_t = y_{wt} - y_{mt}$. If women outperform (underperform) men, then the coefficient estimate for $\beta_{\Delta 0}$ from the k-factor regression model

$$\Delta y_t = \beta_{\Delta 0} + \beta_{\Delta 1} x_{1t} + ... + \beta_{\Delta k} x_{kt} + \varepsilon_{\Delta t}. \tag{3}$$

should be positive (negative) and significantly different from zero.

B. A regression-based replication of the CalTime approach

The two-step version of the *CalTime* methodology discussed so far is widely applied in empirical finance. However, it is possible to completely replicate the results of the calendar time portfolio approach by aid of a pooled linear regression model with Driscoll and Kraay (1998) standard errors as follows:[6]

$$\begin{aligned} y_{ht} = \; & d_{0,0} && + \; d_{0,1}\, x_{1t} && + \; \dots \; + \; d_{0,k}\, x_{kt} \\ + \; & d_{1,0}\, z_{ht}^{(w)} && + \; d_{1,1}\, x_{1t} z_{ht}^{(w)} && + \; \dots \; + \; d_{1,k}\, x_{kt} z_{ht}^{(w)} + v_{ht} \end{aligned} \tag{4}$$

As in expression (1), y_{ht} refers to the month t excess return of investor h. Regression (4)

[6] Note that the Driscoll and Kraay (1998) covariance matrix estimator does only work for balanced panels. However, Hoechle (2007) adjusts the Driscoll-Kraay estimator for use with unbalanced panels and it is this adjusted estimator which we use in the empirical analysis of Section IV.

contains three types of explanatory variables. First, the regression includes the same k market variables x_{st} ($s = 1, ..., k$) as does the second step regression (3) of the *CalTime* approach. The market level variables vary over time but not between the investors. Second, the dummy variable $z_{ht}^{(w)}$ is investor specific (and possibly time-varying). It takes on a value of one if an investor belongs to investor group $j = w$ which constitutes the long position in $\Delta y_t = y_{wt} - y_{mt}$ and zero for investors from group $j = m$. In our previous example, where the researcher wants to investigate whether or not women outperform men, $z_{ht}^{(w)}$ is 1 for women and zero for men. Third and finally, regression (4) contains a full set of interaction terms between $z_{ht}^{(w)}$ and the k market level variables x_{st} ($s = 1, ..., k$).

To replicate the results of the *CalTime* approach when variable $z_{ht}^{(w)}$ is time-varying or when the investor panel is unbalanced, regression (4) has to be estimated by weighted least squares (WLS). As we illustrate empirically in Section IV.*B*., choosing observation weights equal to $w_{ht}^{(j)} = N_{jt}^{-1}$ (with $j = m, w$) completely reproduces the results of the traditional two-step version of the *CalTime* methodology. For mathematical tractability, however, we restrict our formal treatment of the regression based replication of the *CalTime* approach to the case of a balanced panel with N investors, T time periods, and two investor groups $j = m, w$ which are constant over time. Under these assumptions, ordinary least squares (OLS) regression of (4) suffices to reproduce the results of the *CalTime* approach. This is summarized in the following proposition:

Proposition 1 (coefficient estimates). *In a balanced panel with N investors, T time periods, and two investor groups* $j = m, w$*, which are constant over time, it holds true that:*

1. OLS coefficient estimates for $\beta_{\Delta s}$ *(*$s = 0, 1, ..., k$*) in regression (3) are identical to the*

OLS coefficient estimates for $d_{1,s}$ *in regression (4), i.e.,* $\hat{\beta}_{\Delta s} \equiv \hat{d}_{1,s} \;\; \forall s = 0,\ 1,\ ...,\ k$.

2. *For investor group* $j = m$, *OLS coefficient estimates for* β_{ms} *(*$s = 0,\ 1,\ ...,\ k$*) in regression (2) are identical to the OLS coefficient estimates for* $d_{0,s}$ *in regression (4), i.e.,* $\hat{\beta}_{ms} \equiv \hat{d}_{0,s} \;\; \forall s = 0,\ 1,\ ...,\ k$.

Proof: See appendix.

In order to replicate for investor group $j = w$ the coefficient estimates of the *CalTime* approach in (2), we apply the results of Proposition 1 and use $y_{wt} = y_{mt} + \Delta y_t$ to obtain the following corollary:

Corollary 1. $\hat{\beta}_{ws} = \hat{\beta}_{ms} + \hat{\beta}_{\Delta s} = \hat{d}_{0,s} + \hat{d}_{1,s}$ ($s = 0,\ 1,\ ...,\ k$).

However, the regression model in (4) not only replicates the coefficient estimates of the *CalTime* methodology. As we show in the appendix, this regression model may also be used to reproduce the standard error estimates of the *CalTime* approach. This brings us to the following proposition:

Proposition 2 (standard errors). *For a given lag length choice* H *and under the assumptions of Proposition 1, it holds true that:*

1. *Newey and West (1987) standard errors for the coefficient estimates of regression (3) are identical to Driscoll and Kraay (1998) standard errors for the coefficient estimates of* $d_{1,s}$ *(*$s = 0,\ 1,\ ...,\ k$*) in regression (4).*

2. *For investor group* $j = m$, *Newey and West (1987) standard errors for the coefficient estimates of regression (2) are identical to Driscoll and Kraay (1998) standard errors*

for the coefficient estimates of $d_{0,s}$ *(* $s = 0, 1, \ldots, k$ *) in regression (4).*

Proof: See appendix.

Proposition 2 makes intuitive sense because according to Driscoll and Kraay (1998, p. 552) their "covariance matrix estimator is precisely the standard Newey and West (1987) heteroskedasticity and serial correlation consistent covariance matrix estimator, applied to the sequence of cross-sectional averages" of the moment conditions. Thus, one might argue that the calendar time portfolio approach replicates Driscoll-Kraay standard errors by aid of a two-step procedure. Since Driscoll and Kraay (1998) prove that their nonparametric covariance matrix estimator is robust to very general forms of cross-sectional and temporal dependence, Proposition 2 therefore confirms the finding of Lyon, Barber, and Tsai (1999, p. 193) that the *CalTime* approach "eliminates the problem of cross-sectional dependence".

C. Generalizing the calendar time portfolio approach

The original two-step version of the calendar time portfolio approach discussed in Section II.*A.* is limited to the analysis of clearly specified investor groups. Furthermore, since it is impossible to include investor specific explanatory variables (such as the portfolio size) into the second step regression (3) of the *CalTime* approach, the analysis turns out to be rather one-dimensional and it is quite intricate to perform robustness checks. Finally, Loughran and Ritter (2000, p. 362) criticize that by equally weighting each time period instead of each observation, the traditional calendar time portfolio methodology has "low power to identify abnormal returns for events that occur as a result of behavioral timing".[7]

[7] To circumvent this problem, Fama (1998) and Lyon, Barber, and Tsai (1999) suggest to estimate the time-series regression in (3) by aid of weighted least squares (WLS) regression with observation weights set equal to their statistical precision.

In contrast to the traditional two-step version of the calendar time portfolio methodology, the regression based replication of the *CalTime* approach in (4) does not suffer from these shortcomings. In particular, estimating regression (4) with OLS naturally overcomes the critique of Loughran and Ritter (2000). Furthermore, it is straightforward to generalize regression (4). The first possibility is to replace the dichotomous variable $z_{ht}^{(w)}$ by a continuous variable z_{ht} which makes it unnecessary to segregate investors into clear cut groups. Moreover, one can augment regression (4) by including additional investor specific variables. This constitutes a possibility to add control variables to the regression and to perform robustness checks. However, in order to maintain the fundamental structure of regression model (4), it is important to also include all interaction terms between the investor characteristics (z_{qht}) and the market variables (x_{st}). To see this, we rewrite regression (4) by aid of the Kronecker product as[8]

$$\begin{aligned}
y_{ht} &= d_{0,0} + \sum_{s=1}^{k} d_{0,s}\, x_{st} + d_{1,0}\, z_{ht} + \sum_{s=1}^{k} d_{1,s}\, x_{st} z_{ht} + v_{ht} \\
&= \begin{bmatrix} 1 & z_{ht} \end{bmatrix} \otimes \begin{bmatrix} 1 & x_{1t} & \dots & x_{kt} \end{bmatrix} \mathbf{d} + v_{ht} \qquad (5) \\
&= \left(\mathbf{z}_{ht} \otimes \mathbf{x}_t \right) \mathbf{d} + v_{ht}
\end{aligned}$$

where the $2(k+1)\times 1$ dimensional column vector $\mathbf{d}$ contains the regression coefficients, $\mathbf{x}_t$ comprises the market level variables, and $\mathbf{z}_{ht}$ embodies the investor characteristic. From (5) it is obvious that adding an investor specific variable $z_{\mu ht}$ changes the fundamental structure of the regression model unless $z_{\mu ht}$ is part of vector $\mathbf{z}_{ht}$. However, augmenting $\mathbf{z}_{ht}$ with $z_{\mu ht}$ implies that in addition to $z_{\mu ht}$ all interaction terms between $z_{\mu ht}$ and the k market variables

[8] In (5) we exchange dummy variable $z_{ht}^{(w)}$ with variable z_{ht} which is allowed to be continuous.

x_{st} ($s = 1, \ldots, k$) are included in the regression. As a generalization of the *CalTime* approach, we therefore suggest to estimate by OLS the following linear regression model with Driscoll and Kraay (1998) standard errors:[9]

$$
\begin{aligned}
y_{ht} &= \left(\begin{bmatrix}1 & z_{1ht} & \cdots & z_{mht}\end{bmatrix} \otimes \begin{bmatrix}1 & x_{1t} & \cdots & x_{kt}\end{bmatrix}\right)\mathbf{d} + v_{ht} \\
&= d_{0,0} \quad + \quad d_{0,1}\, x_{1t} \quad + \quad \ldots \quad + \quad d_{0,k}\, x_{kt} \\
&+ d_{1,0}\, z_{1ht} \quad + \quad d_{1,1}\, x_{1t} z_{1ht} \quad + \quad \ldots \quad + \quad d_{1,k}\, x_{kt} z_{1ht} \\
&+ \ldots \\
&+ d_{m,0}\, z_{mht} \quad + \quad d_{m,1}\, x_{1t} z_{mht} \quad + \quad \ldots \quad + \quad d_{m,k}\, x_{kt} z_{mht} + v_{ht}
\end{aligned}
\tag{6}
$$

While the k market variables x_{st} in regression (6) vary over time but not across investors, the m investor characteristics z_{qht} can vary across both the time dimension and the cross-section, respectively. It is interesting to notice that the structure of regression (6), to which we henceforth refer to as the "GCT-regression model", is closely related to the structure of Ferson and Schadt's (1996) conditional performance measurement model. However, instead of being time-varying only, the conditional coefficients of the GCT-regression are allowed to vary over both the cross-section and time.

D. Relating the CalTime approach to the CrossReg technique

The first step of the *CrossReg* approach involves estimating for each investor h a time-series regression of y_{ht} on k market variables x_{st} ($s = 1, \ldots, k$) as follows:

$$
y_{ht} = \beta_{0,h} + \beta_{1,h} x_{1t} + \ldots + \beta_{k,h} x_{kt} + \varepsilon_{h,t} \tag{7}
$$

In the second step of the *CrossReg* approach, one then performs a cross-sectional regression

[9] A Stata program which makes it simple to estimate several variants of the GCT-regression model (6) is available from the authors upon request.

of the coefficient estimate for $\beta_{s,h}$ ($s \in \{0, ..., k\}$) from (7) on a set of m investor characteristics z_{qh}:

$$\hat{\beta}_{s,h} = c_{0,s} + c_{1,s} z_{1h} + ... + c_{m,s} z_{mh} + w_{s,h} . \tag{8}$$

By letting z_{qht} be constant over time (i.e., $z_{qht} = z_{qh}$), the relation between the GCT-regression model (6) and the *CrossReg* methodology may be stated as follows:

Proposition 3 (coefficient estimates). *In a balanced panel with N investors and T time periods, OLS coefficient estimates for $c_{q,s}$ in (8) are identical to OLS coefficient estimates for $d_{q,s}$ in (6), i.e., $\hat{c}_{q,s} \equiv \hat{d}_{q,s}$ for $q = 0, 1, ..., m$ and $s = 0, 1, ..., k$.*

Proof: See appendix.

However, because the second step regression of the *CrossReg* methodology only contains one single observation for each investor, it is impossible to estimate the standard errors for the coefficient estimates in (8) such that they are robust to cross-sectional dependence. According to Driscoll and Kraay (1998, p. 559) this is because "unlike in the time dimension, there is no natural ordering in the cross-sectional dimension [...] Thus it would appear that consistent covariance matrix estimation in models of a single cross section with spatial correlations will have to continue to rely on some prior knowledge of the form of these spatial correlations." Put differently, by dividing up the estimation procedure into two steps, the *CrossReg* approach abandons valuable information which can be used to ensure that the statistical results are valid even when cross-sectional dependence is present.[10] In contrast, the GCT-regression

[10] Moreover, the *CrossReg* approach outlined here also fails to adjust the second-stage standard errors for the fact that the dependent variable is estimated.

model preserves any time-series information inherent in the data. This information advantage enables the GCT-regression model to produce standard error estimates that are robust to very general forms of cross-sectional and temporal dependence.

III. Data

The primary database used in this study includes the trades, monthly position statements, and demographic data of 41,719 individual investors. The data comes from a respectable European wholesale bank and covers the period from March 2000 to June 2005. In this section, we describe the investor database and the procedure for computing the individual investors' portfolio returns.

A. Description of the investor database

The investors in our dataset constitute a random sample comprising 90% of the bank's private clients whose main account is denominated in CHF and whose financial wealth at the bank exceeded CHF 75,000 at least once prior to December 2003.[11] Of the sampled investors, 81.3% live in Switzerland, 12.4% are domiciled in Germany, 5.3% reside in another European country, and 1.0% live outside Europe. Most investors maintain a long-term relationship with the bank: 81% of the accounts have been opened prior to December 1995. The attrition rate of the investors is relatively stable and amounts to about 0.2% per month. Yet, the "true" attrition rate is even lower since 2,924 out of 5,370 liquidated bank relationships have occured

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[11] The bank did not provide a 100% sample for confidentiality reasons. However, for all the sampled investors the database contains the entirety of the investors' accounts. A typical investor in our dataset holds two cash accounts and one security account. We are confident that the sampling criteria do not impact on the results. In particular, we deem it unlikely that the investors' stock returns are upward biased as a consequence of the CHF 75,000 threshold. The reason for this is that the sampled investors predominantly invest in Swiss stocks which lost 22% of their value in the time period from March 2000 through December 2003.

due to the account holder's death. The low monthly rate of account closings stands in contrast to the attrition rates observed in comparable studies. Odean (1999), for example, reports a monthly attrition rate of 0.65% in his sample from a large US discount brokerage house and Anderson (2007) one of 1.4% for investors at a Swedish internet brokerage firm.

Descriptive statistics on the number and age structure of investors in our database as well as information on the bank relationships are reported in Panel A of Table I. We report results for men, women, and investors without indicated sex separately as well as results over all investors.[12] Roughly 45% of the sampled investors are female. Amongst shareholders, the proportion of women is slightly lower but nevertheless amounts to 37% (Panel B). As a result, the fraction of female account holders in our dataset is comparable to the 50% share of women observed in the Chinese sample of Feng and Seasholes (2004, 2008). In contrast, women are typically underrepresented in datasets on investors from discount and online brokerage houses (see, e.g., Barber and Odean, 2002; Dorn and Huberman, 2005; Anderson, 2007). We observe a similar pattern in our database when looking at the 1,892 investors with online banking transactions. Amongst this specific investor group, the proportion of female investors is only 23.2%. The average and median bank wealth of the investors in our database amount to CHF 221,520 and CHF 121,967, respectively (not reported in the table).[13]

In this paper, we focus on the common stock investments of the investors. As can be inferred from Panel B in Table I, the median shareholding investor in our database holds 2.60 distinct stocks worth CHF 45,660. However, both the distributions of the portfolio value and the number of stock holdings are skewed to the right. As such, a shareholding investor on

[12] The majority of accounts, for which the sex of the account holder is unknown, belong to the inheritors of an investor who died.

[13] During the sample period, the USD-CHF exchange rate was quite volatile. On average, one USD cost about CHF 1.40. Therefore, the mean and median account value of the investors in our database correspond to about $158,230 and $87,120. On June 2005 (the sample end), the aggregated account value of the investors amounted to CHF 8.82bn which at the time was equal to $6.89bn.

average holds 3.98 stocks worth CHF 138,971. Additional information on value, turnover, and trade size of investors with end of month position holdings in common stocks are reported in Panel B of Table I.

Even though the sampled investors are relatively wealthy, only 27.5% hold month-end positions in common stocks. Hence, the proportion of equity owners is much lower in our sample than the 85.2% stockholder fraction reported by Barber and Odean (2000). However, the low proportion of shareholders in our dataset matches well with the results of Cocca and Volkart's (2006) equity ownership study for Switzerland. This study, which may be compared to the US Survey of Consumer Finances (SCF), reveals that in spring 2000, 29.6% of all Swiss households invested in common stocks. But since then, the overall fraction of shareholding households has declined to a mere 20.0% in spring 2006.[14] However, in contrast to this result for the entirety of Swiss households, the equity ownership study also documents that for households with financial wealth in excess of CHF 100,000 the fraction of equity owners was above 30% over the entire sample period. Consistent with this, Figure 1 shows that in our database shareholders are wealthier on average than investors without stock holdings. Furthermore, Figure 1 reveals that the (median) bank wealth of the sampled investors increases with age. This pattern is in line with the findings of Poterba (2001, 2004) who observes that consumers accumulate financial assets while they are of working age but that they do not reduce financial assets thereafter. Together with the requirement that the investors' total account value has to exceed CHF 75,000 at least once prior to December 2003, this age-wealth relationship (Shorrocks, 1975) results in a disproportionate representation of old investors in the dataset. Correspondingly, Panel A of Table I documents that almost two thirds of

[14] In Germany the fraction of shareholding households is even lower than in Switzerland. According to the Deutsches Aktieninstitut (2006) less than 10% of the German households invested in common stocks during the sample period.

the sampled investors are aged 60 or above in year 2005.

The investors in our database heavily overweight Swiss stocks in their portfolios which confirms the well-known home-bias documented in the literature. It is popular to measure the degree of the home bias as 1 minus the weight invested in foreign countries scaled by the world market weight of foreign countries (e.g., see Kho, Stulz, and Warnock, 2009). Swiss stocks account for roughly 3% of the world market. In unreported tests we find that the average Swiss resident exhibits a home bias of about 80% which corresponds in magnitude with the home bias observed by French and Poterba (1991) and others.[15] To compute the monthly portfolio turnover of the investors, we employ the methodology developed by Barber and Odean (2000, p. 781). Specifically, we define portfolio turnover as the average of the investor's buy and sell turnover during a month.[16] For the average and median shareholder in our database, we observe a monthly turnover rate of 3.16% and 1.18%, respectively. These turnover rates are less than half the size of those reported by Barber and Odean (2000) for the investors at a large US discount broker and almost six times smaller than those found by Anderson (2007) for Swedish online brokerage clients. Hence, the investors in our dataset are much more conservative in trading stocks than those in comparable studies. However, consistent with the findings of these studies, the investors in our database perform slightly more stock purchases (73,098) than sales (70,874), and the average value of stocks sold (CHF 29,400) is higher than the mean value of stocks bought (CHF 24,259).

[15] Detailed results on the weight of CHF denominated stocks in the portfolio by different investor groups are available from the authors upon request.

[16] According to Barber and Odean (2000, p. 781), the buy (sell) turnover in month t is computed as the beginning-of-month t market value of the shares purchased in month $t-1$ (sold in month t) divided by the total market value of the investor's stock portfolio at the beginning of month t. For details on how to compute the monthly portfolio turnover, also see Ivkovic, Sialm, and Weisbenner (2008).

B. Return computations

We use Thomson Financial's Datastream (TDS) to retrieve monthly time-series of stock prices and dividends for all common stocks that are held by the investors.[17] Overall, the investors hold a total of 3,098 distinct stocks of which 1,182 are listed in the United States, 522 in Germany, and 332 in Switzerland. Based on monthly time-series of 61 exchange rates relative to the CHF, we compute the stocks' percentage monthly gross return in CHF as follows:

$$R_{i,t}^{gr} = 100\left(\frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} \frac{S_t^x}{S_{t-1}^x} - 1\right) \tag{9}$$

where $P_{i,t}$ denotes the adjusted closing price of stock i in month t and $D_{i,t}$ contains the sum of dividends paid from stock i during month t. Both $P_{i,t}$ and $D_{i,t}$ are expressed in local currency. Finally, S_t^x refers to the end-of-month t exchange rate (in price notation) between the currency in which the stock is denominated and the CHF.

To compute the gross return of the individual investors' stock portfolios we apply the methodology developed by Barber and Odean (2000). Specifically, for each investor h we estimate the month t gross return [in %] as the value-weighted average return of the beginning-of-month stock holdings:

$$R_{h,t}^{gr} = \sum_{i=1}^{s_{h,t-1}} w_{i,t-1} R_{i,t}^{gr} \tag{10}$$

[17] We refer to "common stocks" as assets with TDS datatype TYPE being equal to EQ. We use this simple definition for common stocks even though Ince and Porter (2006) report that numerous TDS identifiers with TYPE=EQ are closed end funds, REITs, or ADRs rather than common stocks. However, for our dataset the conformity between datatype TYPE in TDS and the bank's own asset classification scheme is very high. For position holdings with TYPE=EQ, the bank also classifies the asset to be an EQUITY in 99.49% of the cases. Similarly, conditional on being in the universe of TDS, 99.68% of the EQUITY position holdings are of TYPE EQ in Thomson Financial's Datastream. Overall, TDS contains the closing prices and dividends for 93.79% of all the investors' EQUITY position holdings.

where $w_{i,t-1}$ is the beginning-of-month t weight of stock i in the portfolio of investor h. It is computed as the beginning-of-month t position value (in CHF) of stock i divided by the aggregated position value (in CHF) of all $s_{h,t-1}$ stock holdings at the time. When computing $R_{h,t}^{gr}$ we make the same simplifying assumptions as do Barber and Odean (2000). Specifically, we presume that all the investors' stock transactions take place on the last day of the month. Thus, we do not consider return components earned between the purchase date of a stock and the end of the month, but we include the stock returns from the actual sale date to the end of the month. Furthermore, with the exception of short-term trades that result in position holdings at the end of a calendar month, we ignore any intramonth trading activity of the investors. Barber and Odean (2000) demonstrate that these simplifying assumptions only cause minor differences in the return calculations even if the portfolio turnover of the investors is high. In our dataset, the turnover rate of the investors is low. Therefore, our return calculations should only marginally be affected by these assumptions.

For each stock transaction, we estimate the transaction costs as the sum of the commissions and a bid-ask spread component. While the bank provides us with the effective commissions (in CHF) of the transactions, we have to estimate the bid-ask spread component of the transaction costs by retrieving the stocks' daily bid and ask prices from TDS and computing the bid-ask spread ($spr_{i,\tau}$) component of the transaction costs for stock i on day τ as

$$spr_{i,\tau} = \frac{P_{i,\tau}^{b} - P_{i,\tau}^{s}}{P_{i,\tau}^{b} + P_{i,\tau}^{s}} \tag{11}$$

where $P_{i,\tau}^{b}$ and $P_{i,\tau}^{s}$ denote the bid and ask price of stock i on day τ, respectively. We use quoted spreads rather than the price impact measure proposed by Barber and Odean (2000, p. 780) because the stock transactions of the investors in our database are small compared to the trades of institutional investors. Therefore, we expect stock prices to be virtually unaffected by the transactions of the sampled investors. Furthermore, unlike transactions of institutional investors which are often executed inside the quoted spreads this is much less so for retail investors (Keim and Madhavan, 1998).[18]

Across all trades, the average (median) total transaction cost of a stock purchase amounts to 1.48% (1.19%) for Swiss stocks, and 2.00% (1.46%) for foreign stocks. For stock sales, the average (median) transaction costs are 1.69% (1.19%) for Swiss stocks, and 3.17% (1.80%) for foreign stocks.

For each investor h, we compute the trade weighted average transaction cost of all purchases ($c_{i,t}^{h,b}$) and sales ($c_{i,t}^{h,s}$) of stock i in month t. Further, we consider the fact that the sampled investors sometimes do not purchase and sell complete stock positions but rather they trade fractions of existing holdings. Therefore, we slightly adjust Barber and Odean's (2000, p. 782) methodology of how to compute the month t net return [in %] of stock i in the portfolio of investor h as follows:

$$(1+R_{i,t}^{h,net}/100)=\left(1+R_{i,t}^{gr}/100\right)\frac{\left(N_{i,t}^{h}-c_{i,t}^{h,s}N_{i,t}^{h,s}\right)}{\left(N_{i,t}^{h}+c_{i,t-1}^{h,b}N_{i,t-1}^{h,b}\right)} \tag{12}$$

In (12), $N_{i,t}^{h}$ denotes the beginning-of-month t number of stocks i in the portfolio of investor h, $N_{i,t}^{h,s}$ refers to the number of stocks sold in month t, and $N_{i,t-1}^{h,b}$ is the number of stocks bought in month $t-1$.[19] If an investor trades the entire stock position in a given month, our definition of $R_{i,t}^{h,net}$ in expression (12) is equal to the one used by Barber and Odean (2000). However, when only parts of an existing stock position are bought or sold, then the stock's

[18] However, if the bid and ask prices are not available from TDS, we compute the bid-ask spread component of the transaction costs as proposed by Barber and Odean (2000, p. 780).

[19] To properly account for stock splits, we use adjusted values for $N_{i,t}^{h}$, $N_{i,t}^{h,s}$, and $N_{i,t-1}^{h,b}$.

net return ($R_{i,t}^{h,net}$) is closer to its gross return ($R_{i,t}^{gr}$). By using (12), we then obtain the month t net return [in %] of investor h 's stock portfolio ($R_{h,t}^{net}$) as

$$R_{h,t}^{net} = \sum_{i=1}^{s_{h,t-1}} w_{i,t-1} R_{i,t}^{h,net} \tag{13}$$

Finally, we also compute for each investor the monthly gross and net excess return [in %] as

$$y_{h,t}^{gr} = R_{h,t}^{gr} - R_{f,t} \quad \text{and} \quad y_{h,t}^{net} = R_{h,t}^{net} - R_{f,t} \tag{14}$$

where $R_{f,t}$ refers to the month t return [in %] on a short-term Eurodeposit in CHF obtained from TDS.

IV. Empirical Analysis

A. An illustration of Propositions 1 to 3

We begin with an exact empirical validation of Propositions 1 through 3. Since all the propositions rely on the assumption of a balanced investor panel with two investor groups that are constant over time, it seems natural to compare the investment performance of women and men. Therefore, we follow Barber and Odean (2001, p. 277) by hypothesizing that after accounting for transaction costs the investment performance of men should be worse than that of women because “men, who are more overconfident than women, trade more than women”. We restrict the analysis to a balanced panel of 2,724 male and 1,432 female investors with stock holdings over the complete sample period from March 2000 through June 2005.

The *CalTime* approach. Using the traditional *CalTime* approach, we test whether or not women outperform men by evaluating the coefficient estimate for the intercept term α_Δ in the time-series regression

$$\Delta y_t^{net} = \alpha_\Delta + \beta_\Delta \mathrm{SPI}_t + \gamma_\Delta \mathrm{World}_t + s_\Delta \mathrm{SMB}_t + h_\Delta \mathrm{HML}_t + \varepsilon_t. \tag{15}$$

Here, SPI_t is the monthly excess return of the Swiss Performance Index and World_t refers to the monthly excess return of the MSCI World total return index orthogonalized by SPI_t. The SMB_t factor denotes the month t return of a zero-investment portfolio which is long in Swiss small caps and short in Swiss large capitalization stocks. Finally, HML_t refers to the monthly return difference between Swiss high and low book-to-market stocks.[20]

The dependent variable, Δy_t^{net}, in regression (15) is the monthly net return of a zero-investment portfolio which is long in the aggregate stock portfolio of women and short in the corresponding portfolio of men. It is computed as

$$\Delta y_t^{net} = y_{wt}^{net} - y_{mt}^{net} \tag{16}$$

$$\text{with} \qquad y_{wt}^{net} = \frac{1}{N_{wt}} \sum_{h=1}^{N_t} \mathrm{Woman}_h \times y_{ht}^{net} \qquad \text{and} \qquad y_{mt}^{net} = \frac{1}{N_{mt}} \sum_{h=1}^{N_t} (1 - \mathrm{Woman}_h) \times y_{ht}^{net}$$

where N_{wt} and N_{mt} refer to the month t number of female and male investors, and $N_t = N_{wt} + N_{mt}$. Woman_h is a dummy variable which is one for women and zero for men and y_{ht}^{net} is the month t net excess return of investor h whose computation has been described in Section III.*B*.

[20] To compute excess returns, we use the return on short-term Eurodeposits in CHF as a proxy for the risk-free investment. The data source is TDS and the Datastream-Mnemonic is SBWSF3L. The SMB_t factor is obtained as the return differential of the Vontobel-Datastream Small Cap Index and the Swiss Market Index (SMI). Finally, the HML_t factor returns are taken from Kenneth French's website: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

The results of estimating the *CalTime* regression in (15) with OLS are displayed in the first two columns of Table II. While the first "CalTime" column contains the coefficient estimates and t-values from estimating regression (15) with $\Delta y_t^{net} = y_{wt}^{net} - y_{mt}^{net}$ as the dependent variable, the second "CalTime" column presents the results of estimating (15) with y_{mt}^{net} as the dependent variable. Both Δy_t^{net} and y_{mt}^{net}, respectively, are computed by aid of equation (16). The reported t-values rely on Newey and West (1987) standard errors which are heteroscedasticity and autocorrelation (up to three lags) consistent. Most importantly, the estimate for the women dummy variable (α_Δ) is positive and significant. We therefore conclude that after accounting for transaction costs, women outperform men by about 1.07% per year on average. This result is consistent with the findings of Barber and Odean (2001).

The GCT-regression model. Propositions 1 and 2 claim that estimating time-series regression (15) with Newey and West (1987) standard errors yields identical results as estimating the following investor-level pooled OLS regression with Driscoll and Kraay (1998) standard errors:

$$
\begin{aligned}
y_{ht}^{net} = {} & \alpha_m + \beta_m \mathrm{SPI}_t + \gamma_m \mathrm{World}_t + s_m \mathrm{SMB}_t + h_m \mathrm{HML}_t \\
& + \alpha_\Delta \mathrm{Woman}_h + \beta_\Delta \mathrm{SPI}_t \times \mathrm{Woman}_h + \gamma_\Delta \mathrm{World}_t \times \mathrm{Woman}_h \\
& + s_\Delta \mathrm{SMB}_t \times \mathrm{Woman}_h + h_\Delta \mathrm{HML}_t \times \mathrm{Woman}_h + v_{ht}
\end{aligned} \tag{17}
$$

By showing that the coefficient estimates and t-stats of columns "CalTime NW87" and "GCT DK98" in Table II coincide, we empirically demonstrate the validity of Propositions 1 and 2.

In contrast to Driscoll and Kraay (1998) standard errors which are robust to very general forms of cross-sectional and temporal dependence, Arellano's (1987) panel-robust standard errors only allow for correlation within clusters but assume independence between the clusters (e.g., individuals). Thus, in Table II the t-values presented in column "GCT A87" are biased when cross-sectional dependence is present. Since cross-sectional dependence is likely to occur in microeconometric panels (e.g., Feng and Seasholes, 2004; Dorn, Huberman, and Sengmueller, 2008; Kumar and Lee, 2006), one should be careful with drawing conclusions from regression models which are based on the assumption of independence between subjects. Indeed, in this specific case we find that panel-robust t-values for the market level variables and the *Woman* dummy are much higher than those in column "GCT DK98". For instance, accounting for cross-sectional dependence in the data scales down the t-value of the *Woman* dummy, which is of key interest for testing whether or not women outperform men, from $t^{A87}_{\text{Woman}} = 4.347$ to $t^{DK98}_{\text{Woman}} = 2.021$.

The *CrossReg* approach. In order to reproduce the coefficient estimate for α_Δ in (17) using the *CrossReg* approach, we first obtain for each investor h the risk-adjusted performance $\hat{\alpha}_h$ from the four-factor time-series regression

$$y^{net}_{ht} = \alpha_h + \beta_h \text{SPI}_t + \gamma_h \text{World}_t + s_h \text{SMB}_t + h_h \text{HML}_t + \varepsilon_{ht}. \tag{18}$$

In the second step, we then test whether or not women outperform men by regressing $\hat{\alpha}_h$ from (18) on the *Woman* dummy:

$$\hat{\alpha}_h = c_0 + c_1 \text{Woman}_h + w_h \tag{19}$$

Table II, column "CrossReg", contains the results from estimating (19) with heteroscedasticity consistent standard errors. As predicted by Proposition 3, the coefficient estimate for c_1 coincides with that for α_Δ in the GCT-regression (17). However, in contrast to the traditional calendar time portfolio approach, which replicates Driscoll and Kraay (1998) standard errors, the *CrossReg* methodology can at best be used to reproduce panel-robust standard errors for the GCT-regression in (17). Therefore, statistical inference from the *CrossReg* approach is valid *if and only if* cross-sectional dependence is absent. However, when cross-sectional dependence is likely to be inherent in the data, then the *CrossReg* methodology should *not* be applied. This is because the two-step algorithm which forms the basis of the *CrossReg* methodology forgoes valuable time-series information which can otherwise be used to ensure validity of the statistical results even when cross-sectional dependence is present.

B. Time-varying investor groups and unbalanced panels

So far our analysis is limited to a balanced panel with two investor groups that are constant over time. In most empirical work, however, these assumptions will not be met. Therefore, we replicate the analysis from Section A. by analyzing an *unbalanced* panel of all 7,140 male and 4,200 female investors with end-of-month positions in common stocks. As before, we follow Barber and Odean (2001) by hypothesizing that after accounting for transaction costs, women outperform men.

In Table III, columns labeled with “CalTime”, we present the results for the traditional *CalTime* approach. As in Table II, the first “CalTime” column contains the coefficient estimates and t-values from estimating regression (15) with $\Delta y_t^{net} = y_{wt}^{net} - y_{mt}^{net}$ as the dependent variable, the second “CalTime” column presents the results of estimating (15) with y_{mt}^{net} as the dependent variable (as defined in equation (16)). As for the balanced panel considered in Section A. and consistent with Barber and Odean (2001), we find that after accounting for transaction costs, women outperform men by a significant return difference of 1.14% per year on average.

In an unbalanced panel with time-varying investor groups, the traditional *CalTime* approach does not weight each observation equally (Loughran and Ritter, 2000). Therefore, estimating the GCT-regression (17) with OLS will not reproduce the results of the calendar time portfolio approach. From Table III this is apparent by observing that the coefficient estimates and t-stats in column “GCT” do not match those of the “CalTime” columns. However, even for the general case of an unbalanced panel with time-varying investor groups it is possible to reproduce the results of the traditional *CalTime* approach by aid of the GCT-regression model in (17). But now we have to explicitly adopt the observation weighting scheme of the *CalTime* approach and estimate (17) with weighted least squares (WLS) rather than with OLS. We therefore set the observation weights equal to[21]

$$\omega_{ht} = \begin{cases} N_{wt}^{-1}\,, & \text{if Woman}_h = 1 \\ N_{mt}^{-1}\,, & \text{otherwise} \end{cases} \tag{20}$$

In Table III, the columns labeled with “GCTw” report the results from estimating regression (17) with WLS. As for the balanced panel case, there is evidence for cross-sectional dependence in the data: Estimating (17) with Driscoll-Kraay standard errors produces t-values for the market variables and the *Woman* dummy which are much smaller (in absolute terms) than those from estimating the GCT-regression (17) with panel-robust standard errors.

Although column “GCTw DK98” demonstrates that the results of the traditional *CalTime* approach may be reproduced with a WLS regression on the investor level, we can not find an econometric reason, why employing the weighting scheme in (20) should yield more appropriate results than estimating (17) with OLS. On the contrary, the weighting scheme in (20) has even been criticized by Loughran and Ritter (2000, p. 363) who argue that “in general, tests that weight firms equally should have more power than tests that weight each time peri-

[21] Alternatively, we could also multiply both sides of regression (17) with $\sqrt{\omega_{ht}}$ and estimate the transformed regression model with OLS.

od equally". As a result, estimating the GCT-regression model in (17) with OLS rather than with WLS naturally resolves Loughran and Ritter's (2000) critique.

C. Multivariate investor characteristics and performance measurement

In this section, we make use of the GCT-regression model's capability to handle continuous and multivariate investor characteristics. Thereby, we use the GCT-regression model to reassess some of the most prominent hypotheses on the performance of private investors first separately and then jointly. All the regressions analyzed in this section embody the following structure:

$$y_{h,t} = (\mathbf{z}_{ht} \otimes \mathbf{x}_t)\mathbf{d} + v_{ht} \tag{21}$$

where, depending on the specific hypothesis, $y_{h,t}$ denotes the investors' gross excess return ($y_{h,t}^{gr}$) or net excess return ($y_{h,t}^{net}$). While the investor characteristics contained in vector $\mathbf{z}_{ht}$ vary among the models, the composition of the market variables in vector $\mathbf{x}_t$ remains unchanged. As in Sections A. and B., we compute the risk-adjusted performance of the investors by specifying $\mathbf{x}_t = [1 \ \ \mathrm{SPI}_t \ \ \mathrm{World}_t \ \ \mathrm{SMB}_t \ \ \mathrm{HML}_t]$.

The first hypothesis to be addressed is derived from Barber and Odean (2000) who find that "investors who hold common stocks directly pay a tremendous performance penalty for active trading". Following Barber and Odean (2000) we therefore expect that:[22]

H1a *The portfolio turnover rate is unrelated to the gross performance of an investor.*

H1b *In contrast, the net performance of an investor decreases with the portfolio turnover.*

[22] The hypotheses we state in this section are *alternative hypotheses*. Therefore, when we "confirm" hypothesis XYZ, we actually mean that the null hypothesis to hypothesis XYZ has to be rejected and thus hypothesis XYZ is accepted.

To empirically examine Hypothesis 1, we estimate regression (21) with $\mathbf{z}_{ht}$ being specified as $\mathbf{z}_{ht} = [1 \;\; \text{TO}_{h,t}]$ where $\text{TO}_{h,t}$ is the month t turnover of investor h's stock portfolio. From Table IV, columns labeled with "H1a" and "H1b", it is apparent that both parts of Hypothesis 1 are confirmed. Specifically, the monthly stock turnover has no significant impact on the gross performance (H1a), but an investor who completely redeploys her stock portfolio lowers the risk-adjusted net return by a sizable and significant 3.69% on average (H1b).

Our second hypothesis is based on Barber and Odean (2001) who report that "since men are more overconfident than women, men will trade more and perform worse than women." We therefore test the following hypothesis:

H2a *The net performance of men is worse than that of women.*

H2b *Men underperform women on a net return basis because they trade more than women.*

By specifying vector $\mathbf{z}_{ht}$ as $\mathbf{z}_{ht} = [1 \;\; \text{Woman}_h]$ and estimating regression (21) with the investors' net excess return ($y_{h,t}^{net}$) as the dependent variable, we find (weak) evidence in favor of hypothesis H2a. As such, column "H2a" of Table IV shows that the risk-adjusted net return of the average women in our dataset exceeds that of a typical men by 1.06% per year $(= 12 \times 0.088\%)$. If hypothesis H2b holds true and women really outperform men simply because they trade less than men, then the coefficient estimate for the Woman_h dummy should become insignificant when the monthly portfolio turnover is included in the regression. To empirically validate hypothesis H2b, we therefore re-estimate the GCT-regression model (21) with $\mathbf{z}_{ht}$ being specified as $\mathbf{z}_{ht} = [1 \;\; \text{Woman}_h \;\; \text{TO}_{h,t}]$. Column "H2b" of Table IV, reveals that augmenting vector $\mathbf{z}_{ht}$ with the investors' portfolio turnover indeed results in an insignificant coefficient estimate for the Woman_h dummy. We therefore conclude that our data (weakly) support Hypothesis 2.

For our third conjecture, we rely on the findings of Barber and Odean (2002) who show that online investors "trade more actively, more speculatively, and less profitably" than phone-based investors. Therefore, we hypothesize that

H3 *Both the gross and net performance of online investors is lower than that of phone-based investors.*

In order to verify this hypothesis, we specify vector $\mathbf{z}_{ht}$ as $\mathbf{z}_{ht} = \left[1 \;\; \text{Online}_h\right]$ where Online_h is a dummy variable with value one for investors who perform stock transactions over an online banking account, and zero otherwise. The results from estimating (21) with $\mathbf{z}_{ht} = \left[1 \;\; \text{Online}_h\right]$ strongly confirm the conjecture. Specifically, columns "H3" of Table IV reveal that on average the risk-adjusted gross (net) return of online investors is a highly significant 2.33% (3.25%) per year lower than for phone-based investors.

The fourth hypothesis is based on Ivkovic, Sialm, and Weisbenner (2008). They report that "skilled investors can exploit information asymmetries by concentrating their portfolios in the stocks about which they have favorable information." We therefore conjecture that

H4a *Both the gross and net performance of an investor are negatively related to the number of stocks in her portfolio.*

We test hypothesis H4a by defining $\mathbf{z}_{ht}$ as $\mathbf{z}_{ht} = \left[1 \;\; \text{NS}_{h,t}\right]$ where $\text{NS}_{h,t}$ is the beginning-of-month t number of stocks in the portfolio of investor h. The columns labeled with "H4a" in Table IV show that the coefficient estimate for $\text{NS}_{h,t}$ is negative and significant. Thus, we can confirm hypothesis H4a. However, this hypothesis is just part of the story in Ivkovic, Sialm, and Weisbenner (2008). In particular, the authors also take into consideration that "fixed costs of trading stocks make it uneconomical for households with limited wealth to hold a large number of securities directly. Moreover, it is likely that some wealthy households might have greater access to information and might possess information processing skills superior to those prevailing among households with smaller accounts, prompting a certain fraction of wealthy investors to concentrate their portfolios in a few investments." Therefore, we refine hypothesis H4a as follows:

H4b *Due to fixed costs of trading stocks, concentrated investors perform particularly well if their portfolio value is large.*

To empirically examine this conjecture, we augment vector $\mathbf{z}_{ht}$ by the natural logarithm of the investors' beginning-of-month t portfolio value $\mathrm{V}_{h,t}$. According to hypothesis H4b we would expect that the coefficient estimate for $V_{h,t}$ is positive and statistically significant. However, as can be seen from Table IV, columns labeled with "H4b", estimating regression (21) with $\mathbf{z}_{ht}$ being specified as $\mathbf{z}_{ht} = \begin{bmatrix} 1 & \mathrm{NS}_{h,t} & \mathrm{V}_{h,t} \end{bmatrix}$ yields a negative and insignificant coefficient estimate for $\mathrm{V}_{h,t}$. As a result, for the investors in our database hypothesis H4b can not be verified.[23]

The fifth and last hypothesis is based on Ivkovich and Weisbenner (2005) and Massa and Simonov (2006) who show that the local stock investments of private investors outperform their remote stock holdings. Hence, we test the following hypothesis:

H5 *Swiss residents' investments in Swiss stocks outperform those of non-Swiss residents.*

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[23] As an alternative, we test hypothesis H4b with vector $\mathbf{z}_{ht} = \begin{bmatrix} 1 & \mathrm{NS}_{h,t} & \mathrm{V}_{h,t} & \mathrm{NSV}_{h,t} \end{bmatrix}$ and test if the coefficient estimate for the interaction term $\mathrm{NSV}_{h,t} = \mathrm{NS}_{h,t} * \mathrm{V}_{h,t}$ is negative and significant. However, the coefficient estimate for $\mathrm{NSV}_{h,t}$ is positive and insignificant. Thus, we must again reject hypothesis H4b.

In order to test Hypothesis 5, we specify vector $\mathbf{z}_{ht}$ as $\mathbf{z}_{ht} = [1 \ \text{Swiss}_h \ \text{WCHF}_{ht} \ \text{SWC}_{ht}]$. Here, Swiss_h is a dummy variable which is 1 for Swiss residents and zero otherwise and WCHF_{ht} refers to the beginning-of-month t weight of Swiss stocks in the portfolio of investor h. If Hypothesis 5 is appropriate, then the coefficient estimate for the interaction variable $\text{SWC}_{ht} = \text{Swiss}_h * \text{WCHF}_{ht}$ should be positive.

The results in the columns labeled with "H5" show that there is no support for Hypothesis 5 in our database. The coefficient estimates for Swiss_h, WCHF_{ht}, and SWC_{ht}, are all insignificant. However, while contradicting the findings in Ivkovich and Weisbenner (2005) and Massa and Simonov (2006), these results are consistent with Seasholes and Zhu (2005) who challenge the results of the previous two studies because they fail to account for cross-sectional dependence in the data. Based on the *CalTime* approach, Seasholes and Zhu (2005) find no evidence for superior information in the local portfolio choices of private investors. By performing a "back-of-the-envelope calculation", they find their standard error estimates to be approximately six times larger than those of Ivkovich and Weisbenner (2005) who estimate cross-sectional regressions. In fact, when we reestimate the regressions in columns "H5" using OLS or panel robust standard errors, and thereby ignore cross-sectional dependence, we find a positive and highly significant coefficient on SWC_{ht} (results not reported). Summarizing, when we ignore cross-sectional correlation, our results are similar to those of Ivkovich and Weisbenner (2005) and Massa and Simonov (2006) and fully support Hypothesis 5. In contrast, when we account for cross-sectional dependence, we do not find evidence for an information advantage of Swiss residents compared to foreigners when investing in Swiss stocks which is consistent with Seasholes and Zhu (2005).

Our empirical analysis so far was restricted to a sequential test of some of the most prominent hypotheses on the performance of private investors. We now take advantage of our

GCT-regression model, which allows us to test all five hypotheses *simultaneously*, and specify vector $\mathbf{z}_{ht}$ as $\mathbf{z}_{ht} = \begin{bmatrix} 1 & \mathrm{TO}_{h,t} & \mathrm{Woman}_h & \mathrm{Online}_h & \mathrm{NS}_{h,t} & \mathrm{Swiss}_h & \mathrm{WCHF}_{h,t} & \mathrm{SWC}_{h,t} \end{bmatrix}$. The results in columns "All" show that the majority of coefficients turn insignificant and the hypothesis that online investors underperform phone-based investors is the only one to remain valid. Hence, Table IV underscores the importance of accounting for cross-sectional correlation *and* testing a number of hypotheses jointly based on the GCT-regression model proposed in this paper. Moreover, these findings question the results in a number of previous studies on private investor behavior and performance which either neglect cross-sectional correlation in the *CrossReg* approach or test each hypothesis separately based on the *CalTime* approach.

V. Conclusion

In this paper, we present a generalization of the calendar time portfolio approach which can easily be implemented in empirical studies. Our methodology is based on the estimation of a linear regression model on the investor level. We show both theoretically and empirically that our "GCT-regression model" is capable to perfectly reproduce the results of the *CalTime* approach. Furthermore, since it relies on the nonparametric covariance matrix estimator of Driscoll and Kraay (1998), the GCT-regression model assures that its statistical results are heteroscedasticity consistent and robust to very general forms of temporal and cross-sectional dependence.

The GCT-regression model resolves several weaknesses of the traditional *CalTime* approach. Most importantly, our methodology allows for the inclusion of continuous and multivariate investor-characteristics in the analysis while preserving the robustness towards cross-sectional dependence. In addition, we resolve the well-known problem of underweighting (overweighting) observations from periods with large (small) cross-sections in unbalanced panels.

In the empirical part of the paper, we apply our GCT-regression model on a new and unique dataset on 41,719 individual investors at a respectable European wholesale bank from March 2000 through June 2005. We compare the results from the GCT-regression model to those obtained from the *CalTime* and *CrossReg* approaches. As expected, we find that the t-values from the *CrossReg* approach, which are based on the assumption of cross-sectional independence, are often three and more times higher than t-values based on Driscoll-Kraay standard errors (which are cross-sectional correlation consistent). Therefore, we conclude that cross-sectional dependence indeed can have severe consequences for the statistical results. Thus, when analyzing microeconometric panel data, it is important to rely on a technique which explicitly accounts for cross-sectional dependence. In addition, we demonstrate the importance of testing several hypotheses jointly in a multivariate setting which is straightforward in our GCT-regression model. Specifically, we show that the results from separate hypothesis tests are largely consistent with those in prior studies, while in a joint test of all five tested hypotheses only the hypothesis that online investors underperform phone-based investors remains valid. These findings question the results in a number of previous studies on private investor performance and underscore the importance of a multivariate setting *and* accounting for cross-sectional correaltion.

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Appendix A Proof of Propositions 1 through 3

A. Proof of Proposition 1

1. Part 1

The dependent variable in regression model (3) is $\Delta y_t = R_{wt} - R_{mt} = y_{wt} - y_{mt}$ which by using matrix algebra can be computed as

$$\Delta y_t = \mathbf{y}_t'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2 = \begin{bmatrix} y_{mt} & \Delta y_t \end{bmatrix}\mathbf{e}_2 \tag{A−1}$$

$$\text{with } \mathbf{Z}' = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ z_1^{(w)} & z_2^{(w)} & z_3^{(w)} & \cdots & z_N^{(w)} \end{bmatrix} = \begin{bmatrix} \iota_N' \\ \mathbf{z}_w' \end{bmatrix},$$

$$\mathbf{y}_t' = \begin{bmatrix} y_{1t} & \cdots & y_{Nt} \end{bmatrix}, \text{ and}$$

$$\mathbf{e}_2' = \begin{bmatrix} 0 & 1 \end{bmatrix}$$

$\mathbf{z}_w'$ is a dummy variable which is 1 if investor h belongs to group $j = w$ and zero otherwise. The second step of the *CalTime* procedure then estimates the k-factor regression model in (3) by OLS. This yields the following coefficient estimates

$$\hat{\beta}_\Delta = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\begin{bmatrix} \Delta y_1 \\ \vdots \\ \Delta y_T \end{bmatrix} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\begin{bmatrix} \mathbf{y}_1'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2 \\ \vdots \\ \mathbf{y}_T'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2 \end{bmatrix}$$

$$= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\begin{bmatrix} \mathbf{y}_1' \\ \vdots \\ \mathbf{y}_T' \end{bmatrix}\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2$$

$$= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\begin{bmatrix} \gamma_1 & \gamma_2 & \cdots & \gamma_N \end{bmatrix}\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2$$

$$= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2 \tag{A−2}$$

where $\gamma_h = \begin{bmatrix} y_{h1} & y_{h2} & \cdots & y_{hT} \end{bmatrix}'$. Now, we turn to the panel regression model in (4) which we write in matrix notation as follows:

$$\begin{bmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1T} \\ y_{21} \\ \vdots \\ y_{NT} \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{k1} z_1^{(w)} \\ 1 & x_{12} & \cdots & x_{k2} z_1^{(w)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{1T} & \cdots & x_{kT} z_1^{(w)} \\ 1 & x_{11} & \cdots & x_{k1} z_2^{(w)} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{1T} & \cdots & x_{kT} z_N^{(w)} \end{bmatrix} \begin{bmatrix} d_{0,0} \\ d_{0,1} \\ \vdots \\ d_{0,k} \\ d_{1,0} \\ \vdots \\ d_{1,k} \end{bmatrix} + \begin{bmatrix} v_{11} \\ v_{12} \\ \vdots \\ v_{1T} \\ v_{21} \\ \vdots \\ v_{NT} \end{bmatrix}$$

or more briefly:

$$vec(\mathbf{Y}) = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_N \end{bmatrix} = \left(\mathbf{Z} \otimes \mathbf{X}\right)\mathbf{d} + \mathbf{v} \tag{A−3}$$

Here, $(\mathbf{Z} \otimes \mathbf{X})$ denotes the Kronecker product of matrix $\mathbf{Z}$ with matrix $\mathbf{X}$. Estimating (A-3) with OLS and applying the calculus rules for the Kronecker product yields the following coefficient estimates for $\mathbf{d}$:

$$\begin{aligned}
\hat{\mathbf{d}} &= \left(\left(\mathbf{Z} \otimes \mathbf{X}\right)'\left(\mathbf{Z} \otimes \mathbf{X}\right)\right)^{-1}\left(\mathbf{Z} \otimes \mathbf{X}\right)' vec\left(\mathbf{Y}\right) \\
&= \left(\left(\mathbf{Z}' \otimes \mathbf{X}'\right)\left(\mathbf{Z} \otimes \mathbf{X}\right)\right)^{-1}\left(\mathbf{Z} \otimes \mathbf{X}\right)' vec\left(\mathbf{Y}\right) \\
&= \left(\mathbf{Z}'\mathbf{Z} \otimes \mathbf{X}'\mathbf{X}\right)^{-1}\left(\mathbf{Z}' \otimes \mathbf{X}'\right) vec\left(\mathbf{Y}\right) \\
&= \left(\left(\mathbf{Z}'\mathbf{Z}\right)^{-1} \otimes \left(\mathbf{X}'\mathbf{X}\right)^{-1}\right)\left(\mathbf{Z}' \otimes \mathbf{X}'\right) vec\left(\mathbf{Y}\right) \\
&= \left(\left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\mathbf{Z}' \otimes \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\right) vec\left(\mathbf{Y}\right)
\end{aligned} \tag{A−4}$$

Next, we use this well-known Lemma from linear algebra (e.g., see Sydsaeter, Strom, and Berck, 2000, p. 146):

Lemma 2. *For any three matrices* $\mathbf{A} \in \mathbb{R}^{r,r}$, $\mathbf{B} \in \mathbb{R}^{r,s}$, *and* $\mathbf{C} \in \mathbb{R}^{s,s}$ *it holds true that* $vec(\mathbf{ABC}) = (\mathbf{C}' \otimes \mathbf{A}) vec(\mathbf{B})$.

and rewrite expression (A-4) as

$$\tilde{\mathbf{d}} = \begin{bmatrix} \hat{d}_{0,0} & \hat{d}_{1,0} \\ \vdots & \vdots \\ \hat{d}_{0,k} & \hat{d}_{1,k} \end{bmatrix} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'[\gamma_1 \quad \gamma_2 \quad \cdots \quad \gamma_N]\left((\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\right)'$$

$$= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{YZ}(\mathbf{Z}'\mathbf{Z})^{-1} \qquad (A-5)$$

Finally, note that the first part of Proposition 1 states that the coefficient estimates from regression model (3) coincide with the coefficient estimates for $d_{1,s}$ in (4). Therefore, we are only interested in the second column of matrix $\tilde{\mathbf{d}}$ in (A-5). To obtain the second column of matrix $\tilde{\mathbf{d}}$ we have to post-multiply (A-5) with $\mathbf{e}_2 = [0 \ \ 1]'$. The resulting expression is identical to (A-2) which completes the proof. ■

2. Part 2

In order to obtain y_{mt}, we have to post-multiply (A-1) by $\mathbf{e}_1 = [1 \ \ 0]'$ rather than by $\mathbf{e}_2 = [0 \ \ 1]'$. Hence, estimating the the k-factor regression model in (2) produces the following coefficient estimates for β_m:

$$\hat{\beta}_m = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{YZ}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_1 \qquad (A-6)$$

Next, we consider that the second part of Proposition 1 states that the coefficient estimates from regression model (2) coincide with the coefficient estimates for $d_{0,s}$ in (4). Therefore, we only need the first column of matrix $\tilde{\mathbf{d}}$ in (A-5). To obtain the respective column, we post-multiply (A-5) with $\mathbf{e}_1$. The resulting expression is identical to (A-6) which completes the proof. ■

B. Proof of Proposition 2

1. Part 1

The formula for computing the Newey and West (1987) covariance matrix with lag length H for the regression model in equation (3) is

$$V^*\left\{\hat{\beta}_\Delta\right\} = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\hat{S}_T\left(\mathbf{X}'\mathbf{X}\right)^{-1}$$

$$\text{with } \hat{S}_T = \sum_{t=1}^{T}\hat{\varepsilon}_{\Delta t}^2\mathbf{x}_t'\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T}\left(\hat{\varepsilon}_{\Delta q}\hat{\varepsilon}_{\Delta q-j}\left(\mathbf{x}_q'\mathbf{x}_{q-j} + \mathbf{x}_{q-j}'\mathbf{x}_q\right)\right) \qquad \text{(A-7)}$$

where $\mathbf{x}_t = [1 \;\; x_{1t} \;\; \ldots \;\; x_{kt}]$ is a $(k+1)$-dimensional row vector. The modified Bartlett weights $w_{j,H} = 1 - j/(H+1)$ ensure positive semi-definiteness of $\hat{S}_T$ and smooth the sample auto-covariance function such that higher order lags receive less weight. Using Corollary 1 we can rewrite residual $\hat{\varepsilon}_{\Delta q}$ in (A-7) as

$$\hat{\varepsilon}_{\Delta q} = N_w^{-1}\sum_{h=1}^{N_w}\hat{\varepsilon}_{hwq} - N_m^{-1}\sum_{h=1}^{N_m}\hat{\varepsilon}_{hmq} \equiv N_w^{-1}W_q - N_m^{-1}M_q \qquad \text{(A-8)}$$

$\hat{\varepsilon}_{hjq}$ denotes the period q residual of investor h from group j where the coefficient estimates $\hat{\beta}_{js}$ ($s = 0, 1, \ldots, k$) are obtained from estimating regression (2) for group j. W_q and M_q refer to the period q sum of the $\hat{\varepsilon}_{hjt}$ for group $j = w$ and $j = m$, respectively. Replacing $\hat{\varepsilon}_{\Delta q}$ in (A-7) by the corresponding term from (A-8) yields

$$\hat{S}_T = \sum_{t=1}^{T} \left(N_w^{-1} W_t - N_m^{-1} M_t \right)^2 \mathbf{x}_t' \mathbf{x}_t \tag{A−9}$$

$$+ \sum_{j=1}^{H} w_{j,H} \sum_{q=j+1}^{T} \left(\left(N_w^{-1} W_q - N_m^{-1} M_q \right) \left(N_w^{-1} W_{q-j} - N_m^{-1} M_{q-j} \right) \left(\mathbf{x}_q' \mathbf{x}_{q-j} + \mathbf{x}_{q-j}' \mathbf{x}_q \right) \right)$$

Next, we turn to the Driscoll and Kraay (1998) covariance matrix estimator for the pooled OLS regression model in (4). For H lags, it has the following structure:

$$\tilde{V}\left\{\hat{\mathbf{d}}\right\} = \left((\mathbf{Z} \otimes \mathbf{X})' (\mathbf{Z} \otimes \mathbf{X}) \right)^{-1} \tilde{S}_T \left((\mathbf{Z} \otimes \mathbf{X})' (\mathbf{Z} \otimes \mathbf{X}) \right)^{-1}$$

with
$$\tilde{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{H} w_{j,H} \left(\hat{\Omega}_j + \hat{\Omega}'_j \right), \tag{A−10}$$

$$\hat{\Omega}_j = \sum_{q=j+1}^{T} \mathbf{h}_q\left(\hat{\mathbf{d}}\right) \mathbf{h}'_{q-j}\left(\hat{\mathbf{d}}\right), \text{ and } \mathbf{h}_q\left(\hat{\mathbf{d}}\right) = \left(\mathbf{Z} \otimes \mathbf{x}_q \right)' \mathbf{v}_q$$

Matrix $(\mathbf{Z} \otimes \mathbf{X})$ has been defined in expression (A-3) above. By using the period q row vector $\mathbf{x}_q = [1 \;\; x_{1q} \;\; \ldots \;\; x_{kq}]$ which contains a constant and all the market level variables, we can rewrite the $(2k+2)$ moment conditions $\mathbf{h}_q(\hat{\mathbf{d}})$ as

$$\mathbf{h}_q\left(\hat{\mathbf{d}}\right) = \left(\mathbf{Z} \otimes \mathbf{x}_q \right)' \mathbf{v}_q = \begin{bmatrix} \sum_{h=1}^{N} v_{hq} \\ x_{1q} \sum_{h=1}^{N} v_{hq} \\ \vdots \\ x_{kq} \sum_{h=1}^{N} v_{hq} \\ x_{1q} \sum_{h=1}^{N_w} \varepsilon_{hwq} \\ \vdots \\ x_{kq} \sum_{h=1}^{N_w} \varepsilon_{hwq} \end{bmatrix} = \begin{bmatrix} \mathbf{x}'_q & \mathbf{x}'_q \\ \mathbf{x}'_q & 0 \end{bmatrix} \begin{bmatrix} W_q \\ M_q \end{bmatrix} \tag{A−11}$$

Next, we define $T_q = W_q + M_q$ and consider the ($(2k+2) \times (2k+2)$) matrix $\hat{\Omega}_j$:

$$\hat{\Omega}_j = \sum_{q=j+1}^{T} \mathbf{h}_q\left(\hat{\mathbf{d}}\right)\mathbf{h}'_{q-j}\left(\hat{\mathbf{d}}\right) = \sum_{q=j+1}^{T}\left(\begin{bmatrix}\mathbf{x}'_q & \mathbf{x}'_q\\ \mathbf{x}'_q & 0\end{bmatrix}\begin{bmatrix}W_q\\ M_q\end{bmatrix}\begin{bmatrix}W_{q-j} & M_{q-j}\end{bmatrix}\begin{bmatrix}\mathbf{x}_{q-j} & \mathbf{x}_{q-j}\\ \mathbf{x}_{q-j} & 0\end{bmatrix}\right)$$

$$= \sum_{q=j+1}^{T}\begin{bmatrix}T_q T_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j} & T_q W_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j}\\ W_q T_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j} & W_q W_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j}\end{bmatrix} \tag{A−12}$$

As a result, matrix $\tilde{S}_T$ in (A-10) can be written in block form as follows:

$$\tilde{S}_T = \begin{bmatrix}\Lambda_1 & \Lambda_2\\ \Lambda_3 & \Lambda_4\end{bmatrix} \tag{A−13}$$

where

$$\Lambda_1 = \sum_{t=1}^{T} T_t^2\mathbf{x}'_t\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T} T_q T_{q-j}\left(\mathbf{x}'_q\mathbf{x}_{q-j} + \mathbf{x}'_{q-j}\mathbf{x}_q\right)$$

$$\Lambda_2 = \sum_{t=1}^{T} T_t W_t\mathbf{x}'_t\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T}\left(T_q W_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j} + T_{q-j}W_q\mathbf{x}'_{q-j}\mathbf{x}_q\right)$$

$$\Lambda_3 = \sum_{t=1}^{T} T_t W_t\mathbf{x}'_t\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T}\left(W_q T_{q-j}\mathbf{x}'_q\mathbf{x}_{q-j} + W_{q-j}T_q\mathbf{x}'_{q-j}\mathbf{x}_q\right)$$

$$\Lambda_4 = \sum_{t=1}^{T} W_t^2\mathbf{x}'_t\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T} W_q W_{q-j}\left(\mathbf{x}'_q\mathbf{x}_{q-j} + \mathbf{x}'_{q-j}\mathbf{x}_q\right)$$

Next, we rewrite matrix $\left((\mathbf{Z}\otimes\mathbf{X})'(\mathbf{Z}\otimes\mathbf{X})\right)^{-1} = (\mathbf{Z}'\mathbf{Z})^{-1}\otimes(\mathbf{X}'\mathbf{X})^{-1}$ as

$$(\mathbf{Z}'\mathbf{Z})^{-1}\otimes(\mathbf{X}'\mathbf{X})^{-1} = \begin{bmatrix}N_m^{-1} & -N_m^{-1}\\ -N_m^{-1} & N_w^{-1}+N_m^{-1}\end{bmatrix}\otimes(\mathbf{X}'\mathbf{X})^{-1}$$

$$= \begin{bmatrix}N_m^{-1}(\mathbf{X}'\mathbf{X})^{-1} & -N_m^{-1}(\mathbf{X}'\mathbf{X})^{-1}\\ -N_m^{-1}(\mathbf{X}'\mathbf{X})^{-1} & (N_w^{-1}+N_m^{-1})(\mathbf{X}'\mathbf{X})^{-1}\end{bmatrix} \tag{A−14}$$

and insert (A-14) into the Driscoll and Kraay (1998) estimator of (A-10) to obtain

$$\tilde{V}\left\{\hat{\mathbf{d}}\right\} = \left((\mathbf{Z}'\mathbf{Z})^{-1}\otimes(\mathbf{X}'\mathbf{X})^{-1}\right)\tilde{S}_T\left((\mathbf{Z}'\mathbf{Z})^{-1}\otimes(\mathbf{X}'\mathbf{X})^{-1}\right) = \begin{bmatrix}\Theta_1 & \Theta_2\\ \Theta_3 & \Theta_4\end{bmatrix} \tag{A−15}$$

where

$$\Theta_1 = N_m^{-2}(\mathbf{X}'\mathbf{X})^{-1}\left(\Lambda_1 - \Lambda_2 - \Lambda_3 + \Lambda_4\right)(\mathbf{X}'\mathbf{X})^{-1}$$

$$\Theta_2 = N_m^{-1}N_w^{-1}(\mathbf{X}'\mathbf{X})^{-1}\left(\Lambda_2 - \Lambda_4\right)(\mathbf{X}'\mathbf{X})^{-1} - \Theta_1$$

$$\Theta_3 = N_m^{-1}N_w^{-1}(\mathbf{X}'\mathbf{X})^{-1}\left(\Lambda_3 - \Lambda_4\right)(\mathbf{X}'\mathbf{X})^{-1} - \Theta_1$$

$$\Theta_4 = N_w^{-2}(\mathbf{X}'\mathbf{X})^{-1}\Lambda_4(\mathbf{X}'\mathbf{X})^{-1} - \Theta_1 - \Theta_2 - \Theta_3$$

To complete the proof of the first part of Proposition 2, we therefore have to show that Θ_4 in the Driscoll-Kraay covariance matrix $\tilde{V}\left\{\hat{\mathbf{d}}\right\}$ from (A-15) coincides with the Newey-West estimator $V^*\left\{\hat{\beta}_\Delta\right\}$ in (A-7). Thus, we simplify the Λ terms in (A-15) as follows

$$\Lambda_1 - \Lambda_2 - \Lambda_3 + \Lambda_4 = \sum\nolimits_{t=1}^{T} M_t^2 \mathbf{x}_t'\mathbf{x}_t + \sum\nolimits_{j=1}^{H} w_{j,H} \sum\nolimits_{q=j+1}^{T} M_q M_{q-j}\left(\mathbf{x}_q'\mathbf{x}_{q-j} + \mathbf{x}_{q-j}'\mathbf{x}_q\right)$$

$$\Lambda_2 - \Lambda_4 = \sum\nolimits_{t=1}^{T}\left(M_t W_t\right)\mathbf{x}_t'\mathbf{x}_t + \sum\nolimits_{j=1}^{H} w_{j,H} \sum\nolimits_{q=j+1}^{T}\left((M_q W_{q-j})\mathbf{x}_q'\mathbf{x}_{q-j} + (M_{q-j}W_q)\mathbf{x}_{q-j}'\mathbf{x}_q\right)$$

$$\Lambda_3 - \Lambda_4 = \sum\nolimits_{t=1}^{T}\left(W_t M_t\right)\mathbf{x}_t'\mathbf{x}_t + \sum\nolimits_{j=1}^{H} w_{j,H} \sum\nolimits_{q=j+1}^{T}\left((W_q M_{q-j})\mathbf{x}_q'\mathbf{x}_{q-j} + (W_{q-j}M_q)\mathbf{x}_{q-j}'\mathbf{x}_q\right)$$

and insert the resulting expressions into Θ_4 from (A-15) to finally obtain

$$\Theta_4 = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\tilde{Q}_T\left(\mathbf{X}'\mathbf{X}\right)^{-1}$$

with

$$\tilde{Q}_T = \sum_{t=1}^{T}\left(N_w^{-1}W_t - N_m^{-1}M_t\right)^2 \mathbf{x}_t'\mathbf{x}_t \qquad \text{(A−16)}$$

$$+\sum_{j=1}^{H} w_{j,H} \sum_{q=j+1}^{T}\left(\left(N_w^{-1}W_q - N_m^{-1}M_q\right)\left(N_w^{-1}W_{q-j} - N_m^{-1}M_{q-j}\right)\right)\left(\mathbf{x}_q'\mathbf{x}_{q-j} + \mathbf{x}_{q-j}'\mathbf{x}_q\right)$$

Since $\tilde{Q}_T$ in (A-16) and $\hat{S}_T$ in (A-9) are identical, this completes the proof. ■

2. Part 2

To prove the second part of Proposition 2, we have to show that Θ_1 from (A-15) is identical to the Newey-West covariance matrix

$$V^*\left\{\hat{\beta}_\Delta\right\} = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\hat{S}_T^m\left(\mathbf{X}'\mathbf{X}\right)^{-1}$$

with $$\hat{S}_T^m = \sum_{t=1}^{T} N_m^{-2}M_t^2\mathbf{x}_t'\mathbf{x}_t + \sum_{j=1}^{H} w_{j,H}\sum_{q=j+1}^{T}\left(N_m^{-2}M_q M_{q-j}\left(\mathbf{x}_q'\mathbf{x}_{q-j} + \mathbf{x}_{q-j}'\mathbf{x}_q\right)\right) \tag{A−17}$$

for the coefficient estimates of the men's portfolio in regression (2). By replacing $\Lambda_1 - \Lambda_2 - \Lambda_3 + \Lambda_4$ with the corresponding term derived above, we obtain the following expression for Θ_1:

$$\Theta_1 = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\tilde{Q}_T^m\left(\mathbf{X}'\mathbf{X}\right)^{-1}$$

with $$\tilde{Q}_T^m = \sum\nolimits_{t=1}^{T} N_m^{-2}M_t^2\mathbf{x}_t'\mathbf{x}_t + \sum\nolimits_{j=1}^{H-1} w_{j,H}\sum\nolimits_{q=j+1}^{T}\left(N_m^{-2}M_q M_{q-j}\left(\mathbf{x}_q'\mathbf{x}_{q-j} + \mathbf{x}_{q-j}'\mathbf{x}_q\right)\right) \tag{A−18}$$

Since $\tilde{Q}_T^m$ in (A-18) and $\hat{S}_T^m$ in (A-17) are identical, this completes the proof. ■

C. Proof of Proposition 3

Let s be fixed to $s = \tilde{s} \in \{0, \ ..., \ k\}$. Then it follows from (A-5) that for the generalized *Cal-Time* regression model in (*GCT*) vector $\hat{\mathbf{d}}_{\tilde{s}}' = \left[\hat{d}_{0,\tilde{s}} \quad \cdots \quad \hat{d}_{m,\tilde{s}}\right]$, which contains the coefficient estimates for $d_{q,\tilde{s}}$, is given by

$$\hat{\mathbf{d}}_{\tilde{s}} = \begin{bmatrix} \hat{d}_{0,\tilde{s}} \\ \vdots \\ \hat{d}_{m,\tilde{s}} \end{bmatrix} = \begin{bmatrix} \hat{d}_{0,0} & \cdots & \hat{d}_{m,0} \\ \vdots & \ddots & \vdots \\ \hat{d}_{0,k} & \cdots & \hat{d}_{m,k} \end{bmatrix}' \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$= \left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\mathbf{Z}'\mathbf{Y}'\mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{e}_{(\tilde{s}+1)} \tag{A−19}$$

Here, $\mathbf{e}_{(\tilde{s}+1)}$ is a $(m+1)\times 1$ vector whose ($\tilde{s}+1$)-th element is equal to one and all other elements are zero.

Next, we turn to the *CrossReg* methodology. Estimating the first step regression for investor h by OLS yields the following coefficient estimates:

$$\hat{\beta}_h = \begin{bmatrix} \hat{\beta}_{0,h} \\ \hat{\beta}_{1,h} \\ \vdots \\ \hat{\beta}_{k,h} \end{bmatrix} = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\gamma_h \tag{A−20}$$

where $\gamma_h' = \begin{bmatrix} y_{h1} & y_{h2} & \cdots & y_{hT} \end{bmatrix}$. Stacking the transpose of all N OLS coefficient vectors from (A-20) produces

$$\begin{bmatrix} \hat{\beta}_{0,1} & \hat{\beta}_{1,1} & \cdots & \hat{\beta}_{k,1} \\ \hat{\beta}_{0,2} & \hat{\beta}_{1,2} & \cdots & \hat{\beta}_{k,2} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\beta}_{0,N} & \hat{\beta}_{1,N} & \cdots & \hat{\beta}_{k,N} \end{bmatrix} = \begin{bmatrix} \gamma_1' \\ \gamma_2' \\ \vdots \\ \gamma_N' \end{bmatrix} \mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1} = \mathbf{Y}'\mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1} \tag{A−21}$$

Thus, we obtain the dependent variable for the second step regression of the *CrossReg* approach by post-multiplying (A-21) with $\mathbf{e}_{(\tilde{s}+1)}$. Therefore, the OLS coefficient vector $\mathbf{c}_{\tilde{s}}$ from the second step regression $\hat{\beta}_{\tilde{s}} = \mathbf{Z}\mathbf{c}_{\tilde{s}} + \mathbf{w}_{\tilde{s}}$ of the *CrossReg* methodology results to be given by

$$\hat{\mathbf{c}}_{\tilde{s}} = \begin{bmatrix} \hat{c}_{0,\tilde{s}} \\ \hat{c}_{1,\tilde{s}} \\ \vdots \\ \hat{c}_{m,\tilde{s}} \end{bmatrix} = \left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\mathbf{Z}'\mathbf{Y}'\mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{e}_{(\tilde{s}+1)} \equiv \hat{\mathbf{d}}_{\tilde{s}} \tag{A−22}$$

Since expression (A-22) is identical to (A-19) for each $\tilde{s} \in \{0, ..., k\}$, this completes the proof. ■

Table I

Description of the investor database

The investor database contains 41,719 investors at a renowned European wholesale bank from March 2000 to June 2005. Most accounts for whom the sex of the account holder is unknown (n.a.) in fact belong to the inheritors of an investor who died. The number of balanced bank relationships is the number of accounts that have been terminated either because an investor decided to move her money to another bank or because the bank wealth of an investor who died during the sample period was distributed amongst her inheritors. The number of new bank relationships lists the number of investors who did not maintain an account at the bank prior to March 2000 but who established an account at the bank between March 2000 and December 2003. The portfolio turnover is the average of the buy and the sell turnover. The buy (sell) turnover in month t is defined as the beginning-of-month t market value of the shares purchased in month $t-1$ (sold in month t) divided by the total market value of the investor's stock portfolio at the beginning of month t.

Panel A. Counts

		Men	Women	n.a.	All
# of investors in the database		22,402	18,730	587	41,719
# of balanced bank relationships		2,822	2,431	117	5,370
# opened bank relationships		2,055	1,661	22	3,738
# investors who died		1,608	1,537	563	3,708
# investors with online banking transactions		1,443	438	11	1,892
# of investors	below 45	3,679	2,069	2	5,750
grouped by age	45 to 59	5,453	3,716	18	9,187
(in 2005)	60 to 74	8,010	5,839	92	13,941
	75 and above	5,253	7,099	474	12,826
	n.a.	7	7	1	15

Panel B. Value, Turnover, and Trade Size of investors with end of month position holdings in common stocks

		Men	Women	n.a.	All
# investors with end of month positions in common stocks		7,140	4,200	165	11,505
Stock portfolio	Mean value (CHF)	147,620	118,615	260,612	138,971
	Median value (CHF)	46,596	43,525	59,508	45,660
	Mean # of stock holdings	4.62	3.71	3.73	4.29
	Median # of stock holdings	2.82	2.18	2.58	2.60
	Mean portfolio turnover p.m. (%)	3.40	2.80	2.07	3.16
	Median portfolio turnover p.m. (%)	1.33	0.94	0.96	1.18
All stock trades	# investors with stock trades	6,114	3,334	138	9,586
	# transactions	105,302	37,199	1,471	143,972
	Mean value of stock trades (CHF)	26,727	26,531	37,813	26,790
	Median value of stock trades (CHF)	13,597	15,574	17,325	14,150
Stock purchases	# investors with stock purchases	4,803	2,205	80	7,088
	# transactions	54,976	17,552	570	73,098
	Mean value of stock buys (CHF)	24,293	23,773	35,903	24,259
	Median value of stock buys (CHF)	12,768	14,686	17,760	13,300
Stock sales	# investors with stock sales	5,326	2,944	132	8,402
	# transactions	50,326	19,647	901	70,874
	Mean value of stock sales (CHF)	29,386	28,994	39,021	29,400
	Median value of stock sales (CHF)	14,660	16,700	16,868	15,225

Table II

An empirical examination of Propositions 1 through 3

This table reports the coefficient estimates and t-values (in parentheses) for three different techniques of how to evaluate the performance of private investors. All results are based on a *balanced* panel of 4,156 private investors with a complete history of end-of-month stock holdings at a renowned European wholesale bank from March 2000 to June 2005. Columns labeled with "*CalTime*" present the results for the calender time portfolio methodology. The dependent variable is the net return of a zero-investment portfolio which is long (short) in the aggregated stock portfolio of all female (male) investors. For ease of comparison with the results of the GCT-regression model in the columns labeled with "*GCT*", the coefficient estimates and t-values of the time-series regression of the calendar time portfolio approach are presented in the rows of the interaction terms (e.g., *SPI*Woman*) rather than in the rows of the actual variables (e.g., *SPI*). The dependent variable in the GCT-regressions is the individual investors' monthly net excess return. Finally, the column labeled *CrossReg* contains the coefficient estimates of a cross-sectional regression. Here, the dependent variable is an investor specific 'alpha' from a Fama and French (1993) like performance measurement model which has independently been estimated for each single investor. The explanatory variables are the monthly excess return of the Swiss Performance Index (*SPI*), the monthly excess return of the MSCI World index (*World*) orthogonalized by SPI, the return of a zero-investment book-to-market portfolio (*HML*), the return of a zero-investment size portfolio (*SMB*), a dummy variable being one if an investor is female (*Woman*), and all interactions between the *Woman* dummy and the aforementioned factor variables. The t-values of the various models are based on the following covariance matrix estimators (*SE type*): *NW87* refers to Newey and West (1987) standard errors, *DK98* stands for Driscoll and Kraay (1998) standard errors, *A87* denotes clustered or panel robust standard errors, and *W80* are White (1980) standard errors. ***,**, and * indicate significance at the 1, 5, and 10 percent levels.

Method	CalTime	CalTime	GCT	GCT	CrossReg
SE type	NW87	NW87	DK98	A87	W80
SPI*Woman	-0.046 ***		-0.046 ***	-0.046 ***	
	(-5.389)		(-5.389)	(-4.346)	
World*Woman	-0.139 ***		-0.139 ***	-0.139 ***	
	(-10.152)		(-10.152)	(-7.855)	
HML*Woman	-0.034 ***		-0.034 ***	-0.034 ***	
	(-3.681)		(-3.681)	(-3.716)	
SMB*Woman	-0.074 ***		-0.074 ***	-0.074 ***	
	(-4.943)		(-4.943)	(-5.778)	
SPI		1.065 ***	1.065 ***	1.065 ***	
		(44.641)	(44.641)	(165.306)	
World		0.446 ***	0.446 ***	0.446 ***	
		(13.186)	(13.186)	(38.565)	
HML		0.145 ***	0.145 ***	0.145 ***	
		(6.232)	(6.232)	(26.291)	
SMB		0.040	0.040	0.040 ***	
		(1.447)	(1.447)	(4.733)	
Woman	0.089 **		0.089 **	0.089 ***	0.089 ***
	(2.021)		(2.021)	(4.347)	(4.347)
Constant		-0.050	-0.050	-0.050 ***	-0.050 ***
		(-0.386)	(-0.386)	(-3.625)	(-3.625)
# obs.	64	64	265,984	265,984	4,156
# clusters			4,156	4,156	
R^2	0.837	0.978	0.468	0.468	0.004
Estimation method	OLS	OLS	pooled OLS	pooled OLS	OLS

Table III

A regression-based replication of the traditional calendar time portfolio approach for unbalanced panels

This table reports the coefficient estimates and t-values (in parentheses) for two techniques of how to evaluate the performance of private investors. All results are based on an *unbalanced* panel of 11,340 private investors with end-of-month stock holdings at a renowned European wholesale bank from March 2000 to June 2005. Columns labeled with "*CalTime*" present the results for the traditional calendar time portfolio methodology. The dependent variable in the time-series regression of the first "*CalTime*" column is the net excess return of a zero-investment portfolio which is long (short) in the aggregated stock portfolio of all female (male) investors. In the second "*CalTime*" column, the dependent variable is the net excess return of the aggregated portfolio of all male investors' stockholdings. The dependent variable in the GCT-regression models is the monthly net excess return of the individual investors. Column "GCT" contains the results of estimating the GCT-regression in (17) with OLS. By contrast, columns labeled with "GCTw" present the results of estimating the GCT-regression with weighted least squares (WLS). Thereby, the observation weights are set equal to the reciprocal value of the number of women (men) with stock holdings in month *t*. The explanatory variables in the regressions are the monthly excess return of the Swiss Performance Index (*SPI*), the monthly excess return of the MSCI World index (*World*) orthogonalized by *SPI*, the return of a zero-investment book-to-market portfolio (*HML*), the return of a zero-investment size portfolio (*SMB*), a dummy variable being one if an investor is female (*Woman*), and all interactions between the *Woman* dummy and the aforementioned factor variables. The t-values of the various models are based on the following covariance matrix estimation techniques (*SE type*): *NW87* refers to Newey and West (1987) standard errors, *DK98* stands for Driscoll and Kraay (1998) standard errors, and *A87* denotes clustered or panel robust standard errors. ***,**, and * indicate significance at the 1, 5, and 10 percent levels.

Method	CalTime	CalTime	GCTw	GCT	GCTw
SE type	NW87	NW87	DK98	DK98	A87
SPI*Woman	-0.0344 ***		-0.0344 ***	-0.0343 ***	-0.0344 ***
	(-3.1144)		(-3.1144)	(-3.1184)	(-4.0055)
World*Woman	-0.1482 ***		-0.1482 ***	-0.1491 ***	-0.1482 ***
	(-10.7340)		(-10.7340)	(-10.9954)	(-9.9839)
HML*Woman	-0.0197 **		-0.0197 **	-0.0192 **	-0.0197 **
	(-2.2248)		(-2.2248)	(-2.2340)	(-2.1603)
SMB*Woman	-0.0645 ***		-0.0645 ***	-0.0651 ***	-0.0645 ***
	(-4.0060)		(-4.0060)	(-3.9909)	(-5.3169)
SPI		1.1046 ***	1.1046 ***	1.1062 ***	1.1046 ***
		(34.2870)	(34.2870)	(34.6479)	(209.5631)
World		0.4957 ***	0.4957 ***	0.4953 ***	0.4957 ***
		(11.0740)	(11.0740)	(10.9755)	(51.1123)
HML		0.2311 ***	0.2311 ***	0.2328 ***	0.2311 ***
		(6.3507)	(6.3507)	(6.4337)	(42.6989)
SMB		0.0261	0.0261	0.0256	0.0261 ***
		(0.7697)	(0.7697)	(0.7537)	(3.4773)
Woman	0.0946 **		0.0946 **	0.0878 *	0.0946 ***
	(2.0644)		(2.0644)	(1.9379)	(3.9098)
Constant		-0.0892	-0.0892	-0.0707	-0.0892 ***
		(-0.5599)	(-0.5599)	(-0.4590)	(-5.7045)
# obs.	64	64	539,879	539,879	539,879
# clusters			11,340	11,340	11,340
R^2	0.777	0.972	0.350	0.354	0.350
Estimation method	OLS	OLS	pooled WLS	pooled OLS	pooled WLS

Table IV

What determines the performance of private investors?

This table reports the coefficient estimates and t-values (in parentheses) from pooled OLS regressions with Driscoll-Kraay standard errors. The standard error estimates are heteroscedasticity consistent and robust to both cross sectional dependence and autocorrelation up to three lags, respectively. The sample consists of 11,340 private investors with end-of-month stock holdings at a renowned European wholesale bank from March 2000 through June 2005. In the regressions, the investors' monthly gross excess return ($y_{h,t}^{gr}$) or their net excess return ($y_{h,t}^{net}$) is the dependent variable and the explanatory variables are obtained by aid of a Kronecker expansion between the factors of a Fama and French (1993) like performance measurement model and a set of investor characteristics (see Section C. for details). The factors of the performance measurement model are the excess return of the Swiss Performance Index (SPI), the excess return of the MSCI World index orthogonalized by the SPI, the return of a zero-investment book-to-market portfolio (HML), and the return of a zero-investment size portfolio (SMB). The investor characteristics considered are the monthly stock turnover ($TO_{h,t}$), a dummy variable being one for women ($Woman_h$), a dummy variable being one for investors who trade stocks over an online banking account ($Online_h$), the beginning-of-month *t* number of stocks in the investors' portfolio ($NS_{h,t}$), the natural logarithm of the beginning-of-month *t* stock portfolio value in CHF ($V_{h,t}$), a dummy variable which is 1 for Swiss residents (*Swiss*), the investors' beginning-of-month *t* portfolio weight of Swiss stocks (*WCHF*), and an interaction term between the Swiss dummy and variable *WCHF* (*Swiss***WCHF*). For brevity, the table only presents the estimation results for the investor characteristics (which are contained in vector $\mathbf{z}_{h,t}$ of regression (21)). ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table IV – continued

Hypothesis	H1a	H1b	H2a	H2b	H3	H3	H4a	H4a	H4b	H4b	H5	H5	All	All
Dependent variable	$y^{gr}_{h,t}$	$y^{net}_{h,t}$	$y^{net}_{h,t}$	$y^{net}_{h,t}$	$y^{gr}_{h,t}$	$y^{net}_{h,t}$	$y^{gr}_{h,t}$	$y^{net}_{h,t}$	$y^{gr}_{h,t}$	$y^{net}_{h,t}$	$y^{gr}_{h,t}$	$y^{net}_{h,t}$	$y^{gr}_{h,t}$	$y^{net}_{h,t}$
$TO_{h,t}$	-0.373	-3.693 **		-3.608 **									0.4413	-2.8334
	(-0.198)	(-2.039)		(-1.998)									(0.2327)	(-1.5600)
$Woman_h$			0.088 *	0.066									0.0096	0.0114
			(1.938)	(1.528)									(0.2798)	(0.3346)
$Online_h$					-0.194 ***	-0.271 ***							-0.1394***	-0.1368***
					(-2.649)	(-3.661)							(-3.2500)	(-3.0508)
$NS_{h,t}$							-0.019 **	-0.020 **	-0.015	-0.018			-0.0121	-0.0115
							(-2.131)	(-2.303)	(-1.168)	(-1.363)			(-1.3002)	(-1.2382)
$V_{h,t}$									-0.015	-0.009				
									(-0.180)	(-0.111)				
Swiss											-0.1733	-0.1837	-0.1290	-0.1365
											(-1.0947)	(-1.1541)	(-0.8343)	(-0.8750)
WCHF											0.3027	0.3842	0.2977	0.3564
											(1.0597)	(1.3436)	(1.0396)	(1.2463)
Swiss*WCHF											0.2247	0.2322	0.1853	0.1803
											(1.1134)	(1.1487)	(0.9322)	(0.9050)
Constant	0.038	0.031	-0.071	0.006	0.058	-0.000	0.107	0.044	0.197	0.077	-0.1959	-0.3229	-0.1430	-0.1888
	(0.317)	(0.256)	(-0.459)	(0.047)	(0.436)	(-0.001)	(0.654)	(0.267)	(0.215)	(0.084)	(-0.7273)	(-1.1913)	(-0.5073)	(-0.6654)
# obs.	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879	539,879
# clusters	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340	11,340
R^2	0.356	0.356	0.354	0.357	0.355	0.355	0.354	0.354	0.363	0.363	0.376	0.376	0.380	0.380

Figure 1

The relationship between age, sex, and financial wealth

The figure displays box plots of the investors' average account value in CHF 1,000 grouped by age (in year 2005), sex, and whether or not they hold common stocks. The sample period is from March 2000 through June 2005. "m" and "f" denote male and female investors, respectively. Investors with (without) position holdings in common stocks are labeled by "S" ("NS"). The middle line in the box plots depicts the median account value of the investor groups and the lower (upper) border line of the boxes show the lower (upper) quartiles of the investor groups' bank wealth.