Aggregate Insider Trading in the S&P 500 and the Predictability of International Equity Premia

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Abstract

We show that aggregate insider trading (AIT) in the S&P 500 is a reliable predictor of the U.S. equity premium, while AIT outside the S&P 500 seems to be uninformative. Aggregate trading of S&P 500 insiders outperforms a broad set of well-established predictors within our sample considering in- and out-of-sample tests for forecast horizons between one and twelve months. In an international setting, we find that AIT based on S&P 500 insiders predicts international equity premia. Contrary to our U.S. based measure of AIT, we do not find any predictive content of G7 country-specific AIT for international equity premia. The informational content of AIT in the S&P 500 for the U.S. and international equity premia stems from the insiders' ability to forecast cash flow news in- and outside the U.S.

JEL classification: D82; G11; G12; G14; G15

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1. Introduction

The predictability of the equity premium is an ongoing debate, attracting attention from practitioners and academics alike.[1] Recent contributions to the equity premium prediction literature show that aggregate information from market participants in the U.S. such as analysts (Li et al., 2013) and short sellers (Rapach et al., 2016) has predictive power for the domestic equity premium. In this paper, we use the informational content of aggregate trades by market participants that are as close to the action as possible: corporate insiders. Prior contributions by Seyhun (1988) as well as Lakonishok and Lee (2001) document that aggregate insider trading (AIT) of U.S. insiders predicts returns in U.S. stock markets. We show that the predictive content of U.S. insiders is driven by S&P 500 insiders. The latter is the most consistent predictor of the U.S. equity premium within our sample, considering in- and out-of-sample tests for forecast horizons between one and twelve months. On the contrary we find that AIT of insiders outside the S&P 500 is not informative for future equity premia. In an international setting, we find that aggregate trading of S&P 500 insiders predicts international equity premia, while non-U.S. aggregate insider trading itself is not informative. The information content of the S&P 500 AIT stems from the insiders' ability to forecast cash flow news in- and outside the U.S.

We start by constructing a monthly measure of U.S.-based AIT from data vendor 2iQ Research. We distinguish between transactions of insiders in S&P 500 firms and all firms in the CRSP universe. Insiders working at large cap firms, represented by S&P 500 companies, are highly connected (Ahern, 2017) and may thus have an informational advantage over other insiders. Our sample period comprises January 2004 until December 2018. After filtering

[1] As a prominent example for a critical contribution, Welch and Goyal (2008) conclude that a broad set of established predictors of the equity premium "would not have helped an investor with access only to available information to profitably time the market". Rapach and Zhou (2013) provide an extensive literature review with more recent results in favor of equity premium predictability.

insider filings in line with the literature we use 929,471 transactions for the CRSP universe; 159,934 of which are transactions from S&P 500 insiders.

We find strong in-sample evidence that aggregate trading by S&P 500 insiders predicts the U.S. equity premium for a one to twelve months horizon. The relation between the aforementioned insider metric and future U.S. equity premia becomes stronger with longer forecast horizons. In contrast, AIT of non-S&P 500 insiders does not have any predictive power. We furthermore compare our results for the S&P 500 AIT with those of a set of 19 predictors (from Welch and Goyal (2008) and more recent papers) and find only three others, implied cost of capital (*ICC*), long-term yield (*LTY*), and treasury bill rate (*TBL*), to also consistently predict U.S. equity premia in-sample across all considered forecast horizons. Out-of-sample tests over the period from January 2010 to December 2018 corroborate the predictive ability of AIT based on S&P 500 insiders.

We next investigate why S&P 500 insiders are able to provide useful information for future equity premia. We employ the Campbell and Shiller (1988) decomposition to identify the source of predictive power. The results show that the predictive content of aggregate trading of S&P 500 insiders can be attributed to insiders' ability to anticipate cash flow news, in line with Jiang and Zaman (2010). The latter is the key driver of AIT's predictive power and relates to existing firm level evidence that insiders are able to predict cash flow realizations of "their" firm on which they trade accordingly (Seyhun, 1992; Piotroski and Roulstone, 2005). Our results for the U.S. suggest that this ability aggregates to the market level and seems to drive the observed link between aggregate insider trading and cash flow news.

Extending our empirical analysis to the G7 countries Canada, France, Germany, Great Britain, and Italy using 2iQ Research insider data, we find that insiders do not possess predictive power on the aggregate level in these countries.[2] In contrast, aggregate trading of S&P 500 insiders conveys predictive information for the equity premia in these countries (*cross-market* analysis), while the reverse does not hold. Decomposing the equity premium of each country shows that the aggregate trading of S&P 500 insiders conveys significant information about international cash flow news. Based on the argument that the correlation between cash flow news from different countries represents a measure of market integration (e.g., Ammer and Mei, 1996) we find that the strength of our cross-market results are related to the degree of market integration.

We contribute to the literature in two aspects. First, our paper documents that U.S. AIT predicts the equity premium in- and out-of-sample. Our results corroborate evidence by Seyhun (1992), Lakonishok and Lee (2001), and Tavakoli et al. (2012) that aggregate trading of U.S. insiders conveys predictive information for future equity premia in the U.S. We add to this literature by documenting, that the predictive content of AIT is higher, when we construct the metric based on transactions of S&P 500 company insiders rather than using all U.S. insiders in the CRSP universe, which is common practice in the literature. This result holds not only for the equity premia itself but also for AIT's ability to anticipate cash flow news. Our finding suggests that the extraction of information from insider transactions can be completed at reduced acquisition and processing costs by focusing on insiders from the largest companies.

Second, we show that AIT of S&P 500 insiders forecasts international equity premia whereas domestic aggregate insider information in countries outside the U.S. cannot. Our results complement findings of Rapach et al. (2013) reporting that U.S. returns have predictive power for foreign stock returns, and Goh et al. (2013) showing that U.S.-based predictors can improve equity premium forecasts in China. Our results add to the existing literature that in

[2] We do not include Japan, because the data set contains an insufficiently small number of filings.

addition to U.S. stock returns and U.S.-based predictors, information from U.S. corporate insiders can be used to forecast international equity premia.

2. Data

Insider transactions are provided by 2iQ Research and span the period 2004 until 2018. We use data from 2iQ Research, because it provides a unified database for the analysis of insider transactions across several countries, including the U.S., Canada, Germany, Italy, France, and the UK. At the same time, the database offers the longest history of insider transactions outside the U.S. Throughout our analyses, we rely on the reporting date of insider transactions in each country to ensure that we assess whether information from publicly available insider filings are valuable for outside investors.

Focusing on the U.S. first,[3] we filter insider filings as follows: First, we delete transactions that have not been reported within the time window given by the Sarbanes-Oxley Act.[4] Second, we exclude insider transactions that are related to employee-stock options because we only consider open-market transactions consistent with the literature (Seyhun, 1992; Ke et al., 2003; Fidrmuc et al., 2013; Cao et al., 2015). Third, we dismiss transactions which are automated trades based on a pre-announced plan an insider discloses. These transactions are to some extent steered by company policies, requiring insiders to pre-announce all transactions (Huddart et al., 2004). Fourth, we delete filings having a missing transaction volume or a missing transaction value.

To measure *AIT*, we use the Lakonishok and Lee (2001) ratio of annual net insider trading to annual total insider trading on a rolling window basis. We use an annual horizon[5] to

[3] We outline the construction of our aggregate insider measure for countries other than the U.S. in Section 4.
[4] The Sarbanes-Oxley act requires insiders to report within two business days.
[5] We report results for shorter aggregation horizons as a robustness check.

aggregate the filtered insider trades in order to mitigate seasonal effects (Seyhun, 1988; Kallunki et al., 2009). Hence, our measure of *AIT* in month *t* is given by

$$AIT_t = \frac{(\sum_{m=t-11}^{t} P_m - S_m)}{(\sum_{m=t-11}^{t} P_m + S_m)}, \quad (1)$$

where P_m and S_m equal the number of trades in month m where an insider purchases or sells securities in her company. To give a simple example: *AIT* equals 1/7 in month *t* if we observe three sales and four purchases in stocks of the insiders' companies over the past 12 months (1/7=(4-3)/(4+3)). The interpretation of the Lakonishok and Lee (2001) ratio is straightforward: the higher *AIT* is, the more bullish insiders are.

We compute our measure of AIT in equation (1) for three clusters of insiders. Specifically, we distinguish between AIT of (i) insiders in S&P 500 firms, (ii) insiders in CRSP firms, and (iii) insiders in CRSP firms that are not included in the S&P 500. The motivation for this distinction is two-fold. On the one hand, we use the equity premium of the S&P 500 as a proxy for the U.S. equity premium in our baseline results and seek to use it as a congruent measure of AIT. On the other hand, the results of this distinction provide evidence on whether insiders of the top firms provide information any different from that of other insiders. We expect insiders working at large cap firms that are highly connected (Ahern, 2017) and internationally well-established to have an information advantage over other insiders. Thus, we expect greater predictive power using insider transactions of S&P 500 firms.

The construction of AIT for the aforementioned insider clusters builds on the index constituents at the end of each month *t*. At the end of each month, we extract the index constituents of the S&P 500 (CRSP index) from Compustat (CRSP data tape). We then aggregate all transactions reported from insiders working at firms that are listed in the S&P 500 (CRSP index) at month *t* according to equation (1) to obtain AIT of S&P 500 (CRSP) insiders in month *t*, AIT_SPX_t (AIT_CRSP_t). The construction of AIT for insiders in CRSP firms that are not included in the S&P 500, *AIT_NON_SPX*, follows the same steps and builds on the respective set of companies at the end of each month.

Our resulting measure of *AIT_SPX* builds on 159,934 transactions over our sample period, 7.62 percent of which are purchases. *AIT_CRSP (AIT_NON_SPX)* builds on 929,471 (769,537) transactions over the sample period of which 30.41 (35.14) percent are purchases. In Figure 1 we plot the time series of *AIT_SPX*.[6] Figure A1 in the appendix shows the times series of *AIT_NON_SPX* and *AIT_CRSP*.

To put our findings into perspective, we also report results for 19 commonly used predictors of the equity premium in the U.S., which we describe in Table 1. These comprise the predictive variables from Welch and Goyal (2008), i.e., the book-to-market ratio, the corporate bond return, the dividend payout ratio, the default return spread, the default yield spread, the dividend price ratio, the dividend yield, the earnings price ratio, the relative equity issuing, inflation rate, the long term bond return and yield, the net equity expansion, the stock market variance, the treasury bill rate, and the term spread.[7] In addition, we use the lagged S&P 500 return (*LRET*),[8] and compute the implied cost of capital (*ICC*) based on Li et al. (2013) as well as the short interest index (*SII*) following Rapach et al. (2016).[9]

[6] We run Ng and Perron (2001) unit root tests which indicate that our measure of aggregate transactions by S&P 500 insiders is stationary, with MZ_{α}^{GLS} and ADF^{GLS} statistics of -23.46 and -3.40 (both significant at the 5 percent level), respectively.
[7] Note that we omit the investment to capital ratio (i/k) because it is not available on a monthly basis.
[8] The lagged U.S. return (Rapach et al., 2013) is mainly included for the analysis of international equity premia in Section 4.
[9] We provide Pearson correlation coefficients for all predictors and our aggregate measures of insider trading in Table A1 in the internet appendix.

3. Empirical Results for the U.S.

We begin our empirical analysis by evaluating the predictive content of the U.S.-based AIT for domestic equity premia first, before investigating the relevance of our predictor for international equity premia in section 4. We highlight the results for the U.S. in this section, to carve out the superior informational content of AIT based on S&P 500 insiders relative to AIT based on CRSP insiders. Additionally, we aim to set the predictive power of AIT_SPX into relation to established as well as recently proposed predictors for the U.S. equity premium. Our analysis in this section follows the general structure of previous research on equity premium predictability by providing in-and out-of-sample evidence for AIT and a broad set of competing predictors. The remainder of our analysis in this section follows Rapach et al. (2016). We compare the forecasting power of AIT in relation to competing predictors by means of forecast encompassing tests and evaluate the economic source of AIT's predictive power by distinguishing whether AIT conveys information about discount rate or cash flow shocks.

3.1. In-Sample Regressions

We assess the predictive content of a variable for the equity premium in the following predictive regression framework:

$$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}. \tag{2}$$

We denote the equity premium over the forecast horizon comprising the next h months by $r_{t:t+h}$, with $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$, which represents the average log excess return of the S&P 500 in excess of the 3-month U.S. Treasury Bill rate over h months.[10] The value of the predictive variable at time t is denoted by x_t.

[10] For robustness, we also use the CRSP index to include relatively small companies and the equal-weighted S&P 500 index.

We estimate Equation (2) using OLS to obtain the slope coefficient estimate $\hat{\beta}$. Note that we report all parameter estimates for standardized values of predictive variables throughout the remaining paper unless otherwise stated. We evaluate the predictive power of variable x by testing the statistical significance of β. We follow Rapach et al. (2016) as well as references therein and use a one-sided hypothesis test, because economic theory suggests the sign of β under predictability. Hence, we test $H_0: \beta = 0$ against $H_1: \beta > 0$.[11] The statistical inference for the parameters in Equation (2) is however problematic due to the Stambaugh (1999) bias and the use of overlapping observations for $h > 1$. We accommodate these challenges using Newey-West standard errors and wild-bootstrapped p-values based on the respective t-statistics.[12]

We report the in-sample coefficient estimates for our three AIT metrics using equation (2) with monthly, quarterly, semi-annual, and annual forecast horizons for the S&P 500 index in Table 2. We observe that the four coefficient estimates for *AIT_SPX* are positive and statistically significant. This first result indicates that a rise in AIT of S&P 500 firms is positively related with the equity premium in the next *h* months on average. The relation of AIT to the future equity premium becomes stronger with longer forecast horizons, as the R^2 statistics increase from 2.8% to 24.1%, which is in line with the results obtained by Seyhun (1992).

Turning to the result for non-SPX insiders (*AIT_NON_SPX*), we observe (except for the 12 months horizon) statistically insignificant results. This suggests that AIT in non-S&P 500 companies is uninformative with respect to future equity premia. The coefficient estimates for

[11] In case a negative relation between the predictor and a future premia is expected, we take the negative of the respective variable such that the null and alternative hypothesis remain valid. The latter applies to the predictors net equity expansion (*NTIS*), treasury bill rate (*TBL*), long-term yield (*LTY*), inflation (*INFL*), and the short interest index (*SII*).

[12] We control for heteroscedasticity and autocorrelation in the standard errors up to lag h and compute the p-value based on 1,000 bootstrap iterations.

all CRSP insiders (*AIT_CRSP*) range in between the respective estimates for *AIT_SPX* and *AIT_NON_SPX*. The relation between *AIT_CRSP* and future equity premia increases with the forecast horizon. However, we observe that the R^2 for *AIT_CRSP* is well below the R^2 of *AIT_SPX* for all forecast horizons. We conclude from our results, that the predictive content is most densely in *AIT_SPX*. The predictive information of *AIT_CRSP* appears to be driven by *AIT_SPX*, but contains *AIT_NON_SPX* noise. The latter seems to be uninformative for future equity premia. These first results are interesting in light of the common practice to compute measures of AIT based on all insiders in the market, which is in our case *AIT_CRSP*.

Examining other predictors from the literature in Table 2, we find *ICC*, *LTY*, and *TBL* to be further predictors, which consistently predict the equity premia in-sample across all four forecast horizons. Overall, our finding suggests that our aggregate measures based on S&P 500 insider trades convey valuable information about the future equity premium.

We test the robustness of our measures' predictive power in several ways. First, we investigate whether the length of the aggregation period of the insider measure matters. This exercise indicates how long insider transactions retain their information value and the robustness thereof for the chosen length of the aggregation period. We vary the aggregation period between 3, 6 and 12 months and show the results for the three insider trading measures in Table 3.[13] Apart from the three-month aggregation period and shorter forecast horizons, results for *AIT_SPX 6M* and *AIT_SPX 12M* are very robust and independent of the aggregation period length. The three-month aggregation period results for shorter forecast horizons are in

[13] While the 3 months AIT is available earlier than the 12 months AIT, we compute the first value for all AIT in December 2003 and thus start all subsequent predictive analyses in January 2005. Note that the 12 months aggregation results replicate results from Table 2 for convenience.

line with Cziraki and Gider (2021) who document that insiders are more likely to close round-trip trades after the 6-month short-swing profits regulation threshold than they are before.[14]

Second, we evaluate whether AIT's predictive power is confined to the equity premium of the S&P 500. Thus, we replace the S&P 500 index with the CRSP index. This broader index reflects the notion that corporate insider information may be particularly insightful for smaller companies because they typically release less public information. Our results in Table A2 of the internet appendix show that our key results remain qualitatively unchanged. Interestingly, S&P 500 insiders also seem to be more informative for the CRSP index compared to all insiders. The consistently stronger results for our insider measure based on S&P 500 insiders corroborate the initial finding that the information content of insider transactions from larger companies is denser and hence a more suitable measure of aggregate insider information. Further, confining the analysis to insiders from the largest companies eases the practical implementation due to lower information gathering and processing costs. Additionally, we observe that two of the three commonly used predictors with significant forecasting ability from Table 2, *LTY* and *TBL*, are not statistically significant anymore for the 12-month forecast horizon.

Third, we also consider the forecast pattern for the equal-weighted S&P 500 index. Results in Table A3 of the internet appendix demonstrate that our baseline results also remain unchanged in this case. In summary, our additional tests provide robust evidence of AIT of S&P 500 insiders being a valuable in-sample predictor of the equity premium. We further scrutinize this finding in an out-of-sample exercise in the next subsection.

[14] Short-swing profits are defined in Section 16(b) of the Securities Exchange Act of 1934 as trades that offset an initial trade within less than 6 months to gain profit. This law further requires profits made within this 6 months period to be returned to the firm.

3.2 Out-Of-Sample Tests

We examine the performance of AIT and other predictors in an out-of-sample setting by running recursive regressions according to Equation (2), without standardizing the predictive variables. Starting in January 2010, we estimate the regression parameters in Equation (2) using only data up to this month and predict the equity premium for the next h months based on the last observation of the predictive variable within the sample. We then expand the estimation window by one month, re-estimate Equation (2) and make our next prediction for the equity premium in the next h months. We repeat this procedure until we forecast the last observation, i.e., the equity premium in December 2018.

We measure the out-of-sample predictive power of an h-step ahead forecast by the out-of-sample R^2 (R^2_{OOS}) proposed by Campbell and Thompson (2008):

$$R^2_{OOS} = 1 - \left(\frac{\sum_{t=1}^{T} (r_{t:t+h} - \hat{r}_{t:t+h})^2}{\sum_{t=1}^{T} (r_{t:t+h} - \bar{r}_{t:t+h})^2} \right), \tag{3}$$

where $r_{t:t+h}$ denotes the realized value of the equity premium over the period from the end of time t to $t+h$, $\hat{r}_{t:t+h}$ the equity premium forecast from the predictive regression at the end of month t for the next h months, and $\bar{r}_{t:t+h}$ is the naïve forecast of the equity premium based on the historical mean using data until period t. The R^2_{OOS} has a positive value if the mean squared prediction error (MSPE) of the predictor is lower than the MSPE of the historical benchmark, reflecting a higher predictive content of the variable. We employ the MSPE-adjusted test statistic developed by Clark and West (2007) to assess the statistical significance of the R^2_{OOS}:

$$f_{t+h} = (r_{t:t+h} - \bar{r}_{t:t+h})^2 - [(r_{t:t+h} - \hat{r}_{t:t+h})^2 - (\bar{r}_{t:t+h} - \hat{r}_{t:t+h})^2] \tag{4}$$

We obtain the p-value for the one-sided t-test that the MSPE of the predictive model is larger than the MSPE of the historical mean by regressing f_{t+h} on a constant and interpret the out-of-sample analysis as in Welch and Goyal (2008), such that robust predictors need to pass both the in- and out-of-sample tests.

Table 4 reports the R^2_{OOS} from forecasting monthly, quarterly, semi-annual, and annual equity premia with our three insider measures. Examining results for the S&P 500 insiders, *AIT_SPX*, *DP*, *DY*, and *LTY* exhibit positive and statistically significant R^2_{OOS}, i.e., outperforming the historical mean, for all four forecast horizons. In particular, for the longest forecast horizon of twelve months, *AIT_SPX* shows the largest R^2_{OOS}. Additionally, since neither *DP* nor *DY* show significant in-sample performance (Section 3.1), our metric based on aggregated trading of S&P 500 insiders (*AIT_SPX*) and *LTY* are the only two predictors that pass both in- as well as out-of-sample tests for all four forecast horizons. Further confirming our in-sample analysis, our two other insider measures (*AIT_NON_SPX* and *AIT_CRSP*), do not perform well over all forecast horizons.

We next run two robustness checks. The first replaces the value-weighted S&P 500 index with the CRSP index (Table A4) and the equal-weighted S&P 500 index (Table A5). Our *AIT_SPX* measure is still among the small set of predictors (besides *DP* and *DY*) that consistently outperforms the historical mean for all forecast horizons from one to twelve months. *LTY* does not pass these robustness checks.

In summary, our out-of-sample analysis confirms the predictive power of aggregate trading based on S&P 500 insiders documented by in-sample results in Section 3.1. Additionally, we find that our insider measure *AIT_SPX* is the only one that passes all in- and out-of-sample tests for all of four considered forecast horizons and robustness checks.

3.3. Forecast Encompassing Tests

We next employ the forecast encompassing test of Harvey et al. (1998) to compare the informational content of the predictive regression forecast based on *AIT_SPX* to the ones based on the 19 competing predictors.[15] We report for each variable the regression coefficient λ of the regression:

$$r_{t:t+h} = (1-\lambda) \cdot \hat{r}^{i}_{t:t+h} + \lambda \cdot \hat{r}^{AIT\_SPX}_{t:t+h}, \tag{5}$$

where λ denotes the weight assigned to the forecast from aggregate trading of S&P 500 insiders and $\hat{r}^{i}_{t:t+h}$ the h months-ahead predictive regression forecast for the equity premium of the S&P 500 from one of the other predictors. The competing h months-ahead predictive regression forecast for the equity premium of the S&P 500 from *AIT_SPX* is denoted by $\hat{r}^{AIT\_SPX}_{t:t+h}$. We report the OLS estimate of λ as well as the statistical significance for the null hypothesis that $\lambda = 0$ against the alternative hypothesis that $\lambda > 0$.[16] If the null hypothesis can be rejected, the AIT-based forecast encompasses the one of the competing predictor. In this case AIT adds to the predictive power of a model containing only the competing predictor

Table 5 reports the results for the regression coefficient estimates $\hat{\lambda}$ for λ in Equation (5). The results show that our *AIT_SPX* metric based on S&P 500 insiders contributes to the vast majority of forecast models tested, which is in line with our previous results. The contribution of the insider measure becomes more important for longer forecast horizons. For instance, for h = 12 months, 15 out of 21 λ estimates equal 1, i.e., the optimal forecast combination only contains information from our insider measure, while the other λ estimates are still statistically significant (except for *BM*). Importantly, we observe that $\hat{\lambda} = 1$ for *AIT_NON_SPX* and *AIT_CRSP* for all forecast horizons. This again corroborates that *AIT_SPX* contains more valuable information for future equity premia than AIT based on other insider groups. Taken together, our results provide evidence that our key predictor based on aggregated S&P 500

[15] We also include the two other insider metrics, *AIT_NON_SPX* and *AIT_CRSP*, to check whether they comprise additional information.
[16] We follow Rapach et al. (2016) and report OLS estimates of λ above one with 1.00.

insider trading has additional information relative to a comprehensive set of established predictors.

3.4. Equity Premium Decomposition

We next investigate the information sources driving the predictive power of S&P 500 insiders for future equity premia. Based on the log-linear approximation of the dividend-price ratio of Campbell and Shiller (1988), we decompose the equity premium in $t+1$ following Campbell (1991) as follows:

$$\begin{aligned} r_{t+1} \approx &\quad E_t r_{t+1} + (E_{t+1} - E_t) \sum_{i=0}^{\infty} \rho^i \, \Delta d_{t+1+i} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \, r_{t+1+j} \\ = &\quad E_t[r_{t+1}] + N_{t+1}^{CF} - N_{t+1}^{DR}, \end{aligned} \tag{6}$$

with E_t being the expected value in t, ρ the average dividend yield in the sample and Δd_t the log dividend growth in t. Equation (6) states that r_{t+1} can be decomposed into the expected excess return in $t+1$ based on information in t, $E_t[r_{t+1}]$, a cash flow news component N_{t+1}^{CF}, and a discount rate news component, N_{t+1}^{DR}. Following Campbell (1991) as well as Ammer and Campbell (1993), we extract the return components using a vector autoregressive model with one lag (VAR(1)):

$$y_{t+1} = \Gamma \cdot y_t + u_{t+1}. \tag{7}$$

The state vector y_{t+1} comprises the equity premium as the first, the log dividend-price ratio as the second, and an additional state variable, augmenting the existing information set as the third variable.[17] Γ is a 3x3 matrix and includes the VAR slope coefficients, while u_{t+1} comprises the systems' disturbances.[18] We define e_1 as a conformable column vector with one

[17] We follow Rapach et al. (2016) and include successively one of the 19 other predictive variables from the existing literature as additional state variables. We also report estimation results without including an additional state variable, which serves as a benchmark specification.
[18] We omit intercepts for notational convenience. This corresponds to estimating the system based on de-meaned observations.

as the first and zeros as remaining elements and take expectations of Equation (7) based on the information set in t to obtain the next periods' expected excess return as

$$E_t r_{t+1} = e_1'(\Gamma \cdot y_t). \tag{8}$$

Following Campbell (1991) we set $\pi' = e_1'\rho\Gamma(I-\rho\Gamma)^{-1}$, which allows us to express discount rate news as

$$N_{t+1}^{DR} = \pi' u_t. \tag{9}$$

We then back out the cash flow news component residually based on Equation (6), which yields

$$N_{t+1}^{CF} = ({e_1}' + \pi')u_t. \tag{10}$$

We estimate the VAR(1) in Equation (7) based on the entire sample using OLS. Plugging the respective estimates for Γ, π, and u_t in Equations (8) - (10) yields estimates for $E_t r_{t+1}$, N_{t+1}^{CF}, and N_{t+1}^{DR}, which we denote by $\hat{E}_t r_{t+1}$, $\widehat{N}_{t+1}^{CF}$, and $\widehat{N}_{t+1}^{DR}$. Using the estimated components of the return decomposition, the forecasting regression equation in Equation (2) can be split into the following three predictive regressions:[19]

$$\hat{E}_t[r_{t+1}] = \alpha_{\hat{E}_t} + \beta_{\hat{E}_t} \cdot AIT\_SPX_t + \varepsilon_{t+1}^{\hat{E}_t}, \tag{11}$$

$$\widehat{N}_{t+1}^{CF} = \beta_{CF} \cdot AIT\_SPX_t + \varepsilon_{t+1}^{CF}, \tag{12}$$

$$\widehat{N}_{t+1}^{DR} = \beta_{DR} \cdot AIT\_SPX_t + \varepsilon_{t+1}^{DR}, \tag{13}$$

Adding the coefficient estimates of $\beta_{\hat{E}_t}$, β_{CF}, and β_{DR} according to Equation (6) yields the estimated slope coefficient in Equation (2), such that

$$\hat{\beta} = \hat{\beta}_{\hat{E}_t} + \hat{\beta}_{CF} - \hat{\beta}_{DR}.$$

Table 6 reports results for the return decomposition using the *AIT_SPX* predictor for S&P 500 insiders. We find that estimates for the sensitivity to conditionally expected returns ($\beta_{\hat{E}_t}$,

[19] We omit intercepts in Equations (12) and (13), because they have a zero mean by construction.

second column) are statistically significant in all specifications, while estimates for the sensitivity to discount rate news ($\hat{\beta}_{DR}$, fourth column) are relatively small and (except in one case) statistically insignificant. The estimated sensitivity to cash flow news ($\hat{\beta}_{CF}$, third column) appears to be the source of our predictor's information content. We find that $\hat{\beta}_{CF}$ contributes on average to more than 42% to the overall predictive content of *AIT_SPX*, rendering an economically meaningful source of information. Further, we observe that the majority of $\hat{\beta}_{CF}$ is statistically significant across the 19 specifications. In contrast to *AIT_SPX*, we find that $\hat{\beta}_{CF}$ is mostly negative in case of insiders outside S&P 500 constituents (*AIT_NON_SPX*, see internet appendix Table A6) or if we consider all U.S. insiders (*AIT_CRSP*, see internet appendix Table A7).[20] The $\hat{\beta}_{DR}$ for the aforementioned groups of insiders is close to zero and statistically insignificant across all specifications.

The results show that the predictive content of aggregate trading of S&P 500 insiders can be attributed to the insiders' ability to anticipate cash flow news (Jiang and Zaman, 2010). Anticipating aggregate cash flow news is the key driver of AIT's predictive power and relates to existing firm level evidence that insiders are able to predict cash flow realizations of "their" firm, on which they trade accordingly (Seyhun, 1992; Piotroski and Roulstone, 2005). Our results suggest that this ability aggregates to the market level and may drive the observed link between AIT and cash flow news. Contrary to *AIT_SPX*, we find that the predictive power of *AIT_NON_SPX* and *AIT_CRSP* is not related to superior information about cash flow or discount rate news.

[20] For this exercise, we replace *AIT_SPX* in Equations (11) to (13) accordingly.

4. International Evidence

In our international analysis, we consider the G7 countries Canada, France, Germany, Great Britain, and Italy.[21] We limit our analysis to the aforementioned countries, because we observe a sufficiently large number of insider filings in these countries to compute our AIT measure, such that it is not biased by idiosyncratic transactions. At the same time, the considered countries represent the economically most relevant developed countries. Insider trading data for the considered countries comes again from 2iQ Research. Following country-specific reporting laws, we exclude transactions reported after four days in Great Britain and five days in Canada, France, Germany, and Italy. We then delete insider transactions that are related to employee-stock options and filings that have a missing transaction volume or a missing transaction value. We construct the *AIT* metrics for each country according to Equation (1) and use AIT_SPX for the U.S. in cross-country analyses. [22]

We compute the equity premia for Canada, France, Germany, Great Britain, and Italy as the local currency total return of the respective MSCI country index in excess of the national currency's three-months interest rate.[23] We obtain the latter from the respective Refinitiv government spot rate yield curves. All of the above-mentioned data range from January 2004 until December 2018, which includes not only the global financial crisis (2007-2008) but also the European sovereign debt crisis (2010-2012) with its impact on the European economy and stock markets.

Data for the local state variables *BILL*, *BM*, *DE*, *DY*, and *EP* in Canada, France, Germany, Great Britain, and Italy come from different sources. *BILL* denotes the domestic three-months interest rate and comes from the respective Refinitiv government spot rate yield

[21] We do not include the G7 country Japan, because the data set comprises only two filings for insider trading in that particular market.
[22] Refer to Figure A2 in the internet appendix for time series graphs for the international insider measures.
[23] We still use the excess return of the S&P 500 as the equity premium for the U.S.

curve. *BM* is the book to market ratio of the respective MSCI country index. *DE* is the log of the 12-month moving sum of dividends minus the log of the 12-month moving sum of earnings of the respective MSCI country index. *EP* (*DY*) denotes the log of the 12-month moving sum of earnings (dividends) paid on an index minus the log of the (lagged) MSCI index price of each country.

4.1. In-sample Regression Results

We investigate the predictive power of aggregate insider trading in an international setting by rerunning Equation (2) and using the international aggregate insider metric of country i at t, $AIT_{i,t}$. We report results for all six countries, where we replicate the S&P 500 insider results of Table 2 for convenience, in Panel A of Table 7. Apart from U.S. insiders, it seems as if insiders from the other five countries do not have predictive power in-sample.

We continue pooling the data in the spirit of Ang and Bekaert (2007), Hjalmarsson (2010), and Rapach et al. (2013). Specifically, pooling the data increases our sample size and thus increases the efficiency of parameter estimates.[24] We evaluate the (average) predictive power of country-specific AIT for the equity premium in the respective country by running the following fixed-effects panel regression:

$$r_{i,t:t+h} = \alpha_i + \beta \cdot AIT_{i,t} + \varepsilon_{i,t:t+h}, \tag{14}$$

with $r_{i,t:t+h}$ being the equity premium of country i from t to $t+h$, α_i the fixed-effect for country i, and $AIT_{i,t}$ the aggregate insider metric of country i at t. We estimate Equation (14) based on all six countries and report the results in Panel B of Table 7.[25] Inference for the parameter estimates is based on the bias-corrected wild bootstrap of Rapach et al. (2013) and

[24] Comparing our baseline in-sample results based on single country regressions in Table 7 confirms our view. Moreover, we observe from appendix Table A8 in the appendix that the parameter estimates across countries are homogeneous except for the domestic insider metric. This alleviates the potential concern that pooling introduces a bias on coefficient estimates.

[25] We report all results excluding the U.S. from the panel in Table A8 of the appendix.

is provided at the one-sided 95% confidence level in squared brackets below the parameter estimates. In what is supportive of results from the individual regressions, we find no significant results, regardless of forecast horizons.

The lack of predictability outside the U.S. appears to be contrary to established Canadian and European firm-level evidence that insiders predict *abnormal* returns of their company.[26] However, we investigate in this paper the predictive content of insiders for the market premium, which is factored out in the aforementioned firm level evidence. Additionally, Rapach et al. (2016) highlight that positive relations on firm level do not necessarily extend to the market level. For example, Kothari et al. (2006) observe that the positive relation between earnings surprises and returns on the firm level is negative on the aggregate market level. We thus conclude, that the inability of Canadian and European AIT to predict local equity premia is not in contrast to standing firm-level evidence.

We continue our analysis by investigating whether the aggregate insider metric of one country conveys predictive information for international equity premia. Our investigation of cross-country predictability follows findings of Rapach et al. (2013), who show that U.S. returns have predictive power for foreign stock returns, because return shocks diffuse only gradually from the U.S. to international stock markets.[27] Following this gradual information diffusion narrative, we investigate whether information from aggregate insider trading in one country helps to predict equity premia in other countries. We evaluate the predictive content of country j's AIT for the equity premia in country i using the following panel regression:

$$r_{i,t:t+h} = \alpha_i + \beta \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}, \tag{15}$$

[26] For instance, see empirical evidence in Fidrmuc et al. (2006) for the United Kingdom, Eckbo and Smith (1998) for Norway, Kallunki et al. (2009) for Sweden, Cziraki et al. (2014) for the Netherlands, Betzer and Theissen (2009) for Germany, and McNally and Smith (2003) for Canada.
[27] In addition, Goh et al. (2013) show that it is beneficial to use U.S.-based predictors to improve forecasts of the equity premium in China.

where $r_{i,t:t+h}$ ($AIT_{j,t}$) comprises the equity premia (aggregate insider trading) of Canada, France, Germany, Great Britain, Italy, and the U.S.

We report the regression results for each country j in Table 8. We find positive and statistically significant estimates as well as economically substantial R^2 in the case of the U.S. AIT (last row). In line with our results in Table 2, parameter estimates and R^2 are increasing with longer forecast horizons. We only find further significantly positive estimates, albeit at smaller magnitude, for the two longer forecast horizons in case of Canadian AIT. The other four markets report insignificant AIT estimates.

We further investigate the cross-country predictive power of aggregate insider trading in a multivariate setup. Specifically, we augment Equation (15) by the insider metrics of all countries,

$$r_{i,t:t+h} = \alpha_i + \sum_{j=1}^{N} \beta_{i,j} \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}, \tag{16}$$

with N denoting the number of countries within the panel, i.e. $N = 6$. We follow Rapach et al. (2013) and estimate Equation (16) by imposing the slope homogeneity restriction $\beta_{i,j} = \bar{\beta}_j$, such that

$$r_{i,t:t+h} = \alpha_i + \sum_{j=1}^{N} \bar{\beta}_j \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}. \tag{17}$$

The parameter estimate $\bar{\beta}_j$ quantifies the average impact of country j's AIT on international equity premia. Panel A of Table 9 reports the OLS parameter estimates and the two-sided 95% confidence intervals based on the bias-corrected wild bootstrap for pooled data by Rapach et al. (2013).[28] Despite moderate multicollinearity issues given the correlations

[28] We report regression results excluding the U.S. equity premium from the panel regression in appendix Table A9.

between the insider metrics, we still find significant parameter estimates for the aggregate US insider trading. Canadian insider information improves forecasting accuracy only for the longest horizon of twelve months.

We further extend the set of control variables, augmenting the regression in Equation (17) with country-specific predictive variables.[29] We follow Rapach et al. (2013) and include the three-month interest rate ($BILL_i$) and the publicly traded companies' dividend yield (DY_i) of country i. Additionally, we include the lagged continuously compounded return of the S&P 500, $LRET$, because Rapach et al. (2013) show that it is an important predictor of international stock markets. We report results in Panel B of Table 9. Aggregate trading of S&P 500 insiders still provides predictive power for forecast horizons of three to twelve months, while they lose forecasting ability for the one-month horizon. The latter finding is mainly driven by the highly significant lagged S&P 500 stock return variable. We also find very strong parameter estimates for the interest rate, while the findings are weaker in case of the dividend yield.

Surprising, at first sight, are the positive results for the insider measure for Great Britain (*AIT_GBR*). Although lacking any predictive power in the individual country (Table 7) and cross-country (Table 8 and Panel A of Table 9) settings, the estimates become significant on at least the 5% level across all forecast horizons. Unreported further analyzes reveal that this is mainly driven by adding the interest rates in Equation (17). We interpret these results in the following way: while GBR insiders were not aware of the sudden effects of the global financial crisis and the European Sovereign debt crisis, they were successful in forecasting the international equity premium in "normal" times, i.e., after controlling for economic shocks by

[29] We again use slope homogeneity restrictions for these additional covariates.

including the interest rate as covariate. This interpretation is also in line with the results of Ozkan und Trzeciakiewicz (2014).

In sum, we find evidence that aggregate trading of S&P 500 insiders also has predictive power for international equity premia. The information content of U.S. AIT extends to forecast horizons beyond one month and thus conveys additional information relative to the lagged U.S. return (Rapach, 2013).

4.2. Out-of-sample Tests

We next evaluate the out-of-sample predictive content of AIT in an international setting. We begin our analysis in a single country setting and proceed in the same manner as in the out-of-sample analysis for the U.S. in Section 3.2. Starting in January 2010, we estimate the regression parameters in Equation (2) using the AIT metric of country i at time t as the predictor to forecast the equity premium of country i over the next h months. We follow the outlined procedure in Section 3.2 until we forecast the last observation, i.e., the equity premium of the respective country in December 2018. We measure the out-of-sample predictive power of an h-step ahead forecast by the corresponding out-of-sample R^2 for each country. We report results for the single-country analyses in Panel A of Table 10. Results for the U.S. replicate the S&P 500 insider results of Table 4 for convenience.[30] Consistent with our in-sample results, we find a positive out-of-sample R^2 only for the U.S.

We next investigate whether the predictive power of U.S. insiders (*AIT_SPX*) also applies to international premia. Specifically, we start in January 2010 and use data of the previous 60 months to estimate the (cross-country) parameters of the panel regression in Equation (15) by

[30] We further investigate the out-of-sample predictive content of the considered predictors in a country-by-country setting, i.e., we do not estimate a panel but rather run predictive regressions recursively in each country. The results are qualitatively similar to our panel results and are available from the authors upon request.

using *AIT_SPX* as predictor for the equity premium of all six countries.[31] We then follow the previously described out-of-sample approach and show the results in Panel B of Table 10. We find that S&P 500 insiders predict the equity premia of all the other considered countries for a forecast horizon of twelve months. This predictive power is strongest for Great Britain, i.e., applies to all four forecast horizons. Closely behind in terms of forecasting ability ranking (except the one-month ahead period) are France, Canada, and Germany (except the one- and three-month ahead periods). Predictions for the equity premia in Italy are only significant for the longest forecast horizon.

4.3. International Equity Premium Decomposition

Our previous results show, that AIT of S&P 500 insiders has predictive information not only for U.S. but also for international equity premia. We investigate in this section the insiders' source of information for international equity premia and extend the equity premium decomposition for the U.S. in Section 3.4. to our international panel setup. We decompose the equity premium of each country by estimating the VAR(1) in Equation (7) using OLS. We include the local state variables *BILL*, *BM*, *DE*, *DY*, *EP*, and *LRET* successively.[32] We then plug the respective parameter estimates into Equations (8) – (10) to back out estimates of the next periods' expected excess return $\hat{E}_t[r_{i,t+1}]$, the cash flow news $\hat{N}^{CF}_{i,t+1}$, and the discount rate news component $\hat{N}^{DR}_{i,t+1}$ for each country i. We then run the following panel regressions to decompose the estimate of β in Equation (15) into the expected excess return in $t+1$ based on information in t, a cash flow news, and a discount rate news component:

$$\hat{E}_t[r_{i,t+1}] = \alpha_{\hat{E}_t} + \beta_{\hat{E}_t} \cdot AIT\_SPX_t + \varepsilon^{\hat{E}_t}_{i,t+1}, \tag{18}$$

[31] We do not use the other country-specific insider metrics, because they do not have any forecasting ability within their own country.
[32] Note that we cannot include the full list of covariates as in the U.S. analysis of Section 3.4 due to data limitations for the international markets.

$$\widehat{N}_{i,t+1}^{CF} = \beta_{CF} \cdot AIT\_SPX_t + \varepsilon_{i,t+1}^{CF}, \quad (19)$$

$$\widehat{N}_{i,t+1}^{DR} = \beta_{DR} \cdot AIT_{SPX_t} + \varepsilon_{i,t+1}^{DR}. \quad (20)$$

Table 11 reports the slope coefficient estimates in Equations (18) – (20). Our results show that the aggregate trading of S&P 500 insiders conveys significant information about future international cash flow news (column 3) given that β_{CF} is the largest estimate in six out of seven cases. To check robustness of these results, i.e., whether they are not only driven by U.S. insiders being able to predict the S&P 500 premia, we report decomposition results excluding the U.S. from the panel in Table A10 of the appendix. The results are qualitatively similar and hence alleviate such concerns.

Yet, the question arises why U.S. insiders possess such information, in particular, that they seem to know more than the domestic insiders. Our next test builds on the argument that the correlation between cash flow news from different countries represents a measure of market integration (e.g., Ammer and Mei, 1996). We calculate the Pearson correlation coefficient of the estimated cash flow news, $\widehat{N}_{i,t+1}^{CF}$, between the six countries in our sample from the above decomposition analysis. Table 12 reports the results. To shed light on the different forecasting ability of U.S. insiders on international equity premia, we are particularly interested on the last row. We find that cash flow news correlations are lowest between the U.S. and Italy, which is in line with the out-of-sample results of Table 10. The second lowest correlation is between the U.S. and Canada, which also confirms the prior findings. Hence, weaker cross-market results can be, at least in part, explained by a more moderate degree of market integration.

5. Conclusion

In this paper we show that U.S.-based AIT predicts U.S. equity premia in- and out-of-sample. The informational content is concentrated in transactions reported by insiders working at S&P 500 firms representing the largest and most connected companies. AIT based on firms outside the S&P 500, which is commonly considered in the literature, seems to be uninformative. The predictive power of AIT for U.S. equity premia compares favorably to the informational content of a broad set of established and recently proposed predictors. The predictive content stems from the insiders' ability to forecast cash flow news.

The informational content of AIT based on S&P 500 insiders for future equity premia extends to international markets (G7 countries ex Japan). The aforementioned predictive power is stronger for countries with a higher degree of market integration with the U.S. Contrary to our U.S.-based measure of AIT, we do not find any predictive content of G7 country-specific AIT for international equity premia. The informational content of our U.S.-based insider measure for international equity premia stems from the insiders' ability to forecast cash flow news outside the U.S.

Overall, we have provided empirical evidence that AIT of S&P 500 firms is a reliable predictor for equity premia in- and outside the U.S., because it is based on information which is revealed by particularly well-informed market participants. Investors should focus on AIT from S&P 500 firms to forecast U.S. and international equity premia.

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Figure 1: Time Series of Aggregate Insider Transaction Metrics

The graph shows the time series of *AIT_SPX* (S&P 500 insiders) in the U.S. over the period from January 2005 until December 2018 (left y-axis). The dotted line (right y-axis) reports the performance of the S&P 500 index (January 2005 equals 1).

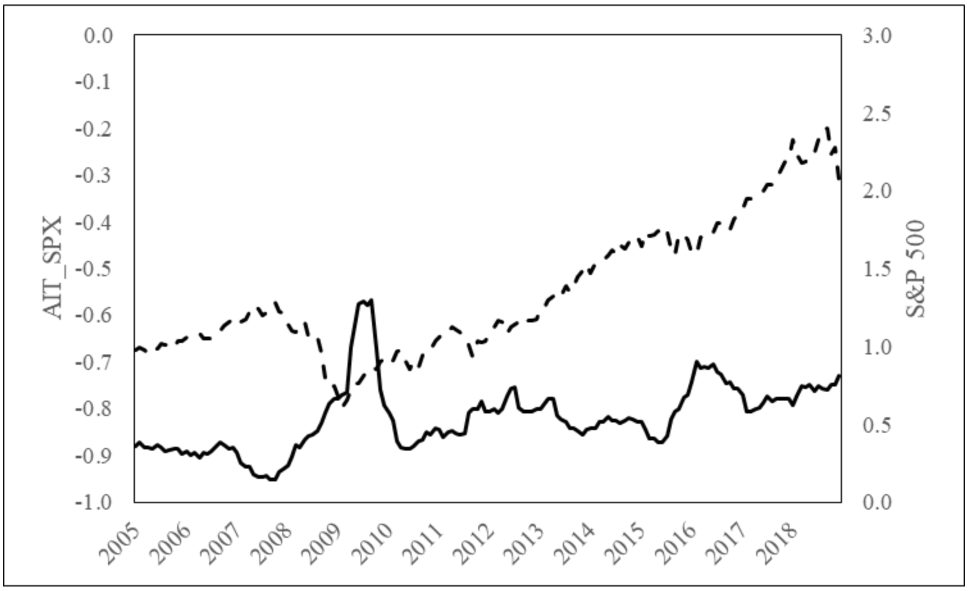

Table 1: Data descriptions – U.S. Predictors

This table reports the considered predictive variables, their data source, and a brief description.

#	Predictor	Abbreviation	Data source	Description
1	Aggregate Insider Trading of S&P 500 Level A insiders	AIT	2iQ	Aggregate insider trading as measured in equation (1) of S&P 500 insiders
2	Aggregate Insider Trading of all U.S. Level A insiders	AIT_NON_SPX	2iQ	Aggregate insider trading as measured in equation (1) of all non-S&P 500 U.S. insiders
3	Aggregate Insider Trading of all U.S. Level A insiders	AIT_CRSP	2iQ	Aggregate insider trading as measured in equation (1) of all insiders at CRSP firms.
4	Book-to-market ratio	BM	A. Goyal	Ratio of book value to market value on the Dow Jones Industrial Average
5	Corporate bond return	CRPR	A. Goyal	Long-term corporate bond return
6	Dividend payout	DE	A. Goyal	Log of the 12 month moving sum of dividends minus the log of the 12 month moving sum of earnings on the S&P 500
7	Default return spread	DFR	A. Goyal	Long-term corporate bond return minus long-term government bond return
8	Default yield spread	DFY	A. Goyal	Spread between BAA and AAA-rated corporate bond yields
9	Dividend price ratio	DP	A. Goyal	Log of the 12 month moving sum of dividends paid on an index minus the log of stock prices on the S&P 500
10	Dividend yield	DY	A. Goyal	Log of a 12 month moving sum of dividends paid on an index minus the log of lagged stock prices on the S&P 500
11	Earnings price ratio	EP	A. Goyal	Log of a 12 month moving sum of earnings on an index minus the log of stock prices on the S&P 500
12	Percent equity issuing	EQIS	J. Wurgler and Fed Bulletin	Ratio of gross share issues to total gross share and debt issues as in Baker and Wurgler (2000)
13	Implied cost of capital	ICC	Compustat, I/B/E/S	Implied Cost of Capital of Li et al. (2013)

Table 1 continued

#	Predictor	Abbreviation	Data source	Description
14	U.S. inflation rate	INFL	A. Goyal	U.S. Consumer Price Index (All Urban Consumers)
15	Lagged return of the S&P 500	LAG	Bloomberg	Lagged return of the S&P 500 total return index
16	Long-term rate of return	LTR	A. Goyal	Long-term government bond return
17	Long-term yield	LTY	A. Goyal	Long term government bond yield
18	Net equity expansion	NTIS	A. Goyal	Ratio of a 12 month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization
19	Short interest index	SII	Compustat, CRSP	Standardized equally weighted short interest as defined in Rapach et al. (2016)
20	Stock variance	SVAR	A. Goyal	Sum of squared daily returns of the S&P 500 total return index
21	Treasury bill rate	TBL	A. Goyal	Three months treasury bill rate
22	Term spread	TMS	A. Goyal	Long-term government bond yield minus treasury bill rate

Table 2: In-Sample Regression Results for the S&P 500 Equity Premium

This table reports the OLS estimate of β and R^2 statistic for the predictive regression model,
$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where x_t denotes the predictive variable at t and $r_{t:t+h}$ denotes the equity premium of the S&P 500 for the forecast horizon of $h = 1, 3, 6,$ and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The predictive variables in the first column are standardized to have a mean of zero and standard deviation of one; (-) imply that we take the negative of the respective predictor. We refer to Table 1 for variable definitions and descriptions. The regression coefficients are estimated over the period from January 2005 until December 2018. Parentheses below parameter estimates report heteroskedasticity- and autocorrelation-robust standard errors up to lag length h. Significance is based on one-sided wild-bootstrapped p-values and provided at the 1%, 5%, and 10% level (denoted by ***, **, and *).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
AIT_SPX	0.68***	2.83	0.71***	8.00	0.70***	12.95	0.69*	24.10
	(2.80)		(3.81)		(3.67)		(2.14)	
AIT_NON_SPX	0.13	0.11	0.15	0.34	0.18	0.87	0.39**	7.75
	(0.31)		(0.39)		(0.57)		(2.56)	
AIT_CRSP	0.42*	1.11	0.44*	3.01	0.45**	5.34	0.60**	18.32
	(1.32)		(1.77)		(2.47)		(2.88)	
BM	0.41	1.05	0.59*	5.49	0.79**	16.51	0.70*	25.02
	(1.16)		(2.05)		(2.72)		(1.95)	
CRPR	0.85	4.49	0.14	0.29	0.30*	2.37	0.17*	1.40
	(1.52)		(0.37)		(1.44)		(1.73)	
DE	0.14	0.13	0.27	1.12	0.33	2.84	0.26	3.46
	(0.28)		(0.69)		(1.22)		(2.04)	
DFR	0.52	1.63	0.27	1.17	0.32	2.63	0.19	1.80
	(0.83)		(0.77)		(1.35)		(1.43)	
DFY	-0.33	0.66	-0.10	0.15	0.16	0.66	0.25	3.20
	(-0.54)		(-0.18)		(0.45)		(1.64)	
DP	0.21	0.26	0.32	1.60	0.44	5.17	0.47*	11.32
	(0.34)		(0.63)		(1.45)		(3.90)	
DY	0.39	0.95	0.41	2.65	0.50	6.56	0.51**	13.24
	(0.73)		(0.98)		(2.09)		(4.07)	
EP	-0.11	0.08	-0.23	0.83	-0.27	1.89	-0.17	1.55
	(-0.23)		(-0.64)		(-0.95)		(-1.05)	
EQIS	-0.92	5.24	-0.67	7.03	-0.53	7.42	-0.12	0.71
	(-1.70)		(-1.61)		(-1.68)		(-0.67)	
ICC	0.48*	1.43	0.45*	3.14	0.52**	7.21	0.62**	19.33
	(1.53)		(1.66)		(2.38)		(2.73)	
INFL (-)	-0.35	0.75	-0.24	0.93	0.21	1.12	0.30**	4.64
	(-1.11)		(-0.61)		(0.85)		(1.81)	
LRET	0.58	2.04	0.27	1.18	0.14	0.51	0.08	0.31
	(1.25)		(0.81)		(0.74)		(0.55)	
LTR	0.43	1.14	-0.06	0.05	0.07	0.12	0.03	0.04
	(1.20)		(-0.21)		(0.50)		(0.32)	
LTY (-)	0.63***	2.41	0.60**	5.63	0.64**	10.85	0.57*	16.51
	(2.27)		(2.26)		(2.18)		(2.05)	
NTIS (-)	-0.70	3.01	-0.74	8.70	-0.67	11.92	-0.48	11.53
	(-1.45)		(-1.59)		(-1.48)		(-1.30)	
SII (-)	0.65	2.56	0.88*	12.09	0.96	24.30	0.73	27.07
	(1.43)		(1.92)		(1.98)		(2.00)	
SVAR	-0.98	5.84	-0.63	6.19	-0.10	0.26	0.11	0.64
	(-2.14)		(-2.08)		(-0.45)		(1.13)	
TBL (-)	0.38*	0.89	0.39**	2.44	0.46**	5.54	0.59*	17.90
	(1.55)		(1.87)		(2.10)		(2.08)	
TMS	0.11	0.07	0.08	0.11	0.18	0.83	0.42*	8.82
	(0.33)		(0.28)		(0.78)		(2.35)	

Table 3: Predictive Content of Aggregate Insider Trading with Respect to the Aggregation Period

This table reports the OLS estimate of β and R^2 statistic for the predictive regression model,
$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where x_t denotes the predictive variable at t and $r_{t:t+h}$ denotes the equity premium of the S&P 500 for the forecast horizon of $h = 1, 3, 6,$ and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. In case of the three aggregate insider measures, x_t denotes aggregate insider trading at different aggregation periods (3, 6, and 12 months). The predictive variables in the first column are standardized to have a mean of zero and standard deviation of one. We refer to Table 1 for variable definitions and descriptions. The regression coefficients are estimated over the period from January 2005 until December 2018. Parentheses below parameter estimates report heteroskedasticity- and autocorrelation-robust standard errors up to lag length h. Significance is based on wild-bootstrapped p-values and provided at the 1%, 5%, and 10% level (denoted by ***, **, and *).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
AIT_SPX 3M	-0.29	0.50	0.06	0.07	0.48*	5.97	0.47***	11.37
	(-0.56)		(0.17)		(2.77)		(3.96)	
AIT_SPX 6M	0.45	1.22	0.66**	6.86	0.75***	14.82	0.63***	19.90
	(0.91)		(2.48)		(5.54)		(3.75)	
AIT_SPX 12M	0.68***	2.83	0.71***	8.00	0.70***	12.95	0.69*	24.10
	(2.80)		(3.81)		(3.67)		(2.14)	
AIT_NON_SPX 3M	-0.23	0.33	-0.03	0.01	0.08	0.18	0.09	0.43
	(-0.49)		(-0.07)		(0.27)		(0.44)	
AIT_NON_SPX 6M	0.09	0.04	0.12	0.24	0.14	0.54	0.16	1.35
	(0.19)		(0.32)		(0.40)		(0.81)	
AIT_NON_SPX 12M	0.13	0.11	0.15	0.34	0.18	0.87	0.39**	7.75
	(0.31)		(0.39)		(0.57)		(2.56)	
AIT_CRSP_3M	-0.13	0.11	0.14	0.30	0.32	2.62	0.29*	4.30
	(-0.28)		(0.39)		(1.57)		(2.22)	
AIT_CRSP_6M	0.32	0.63	0.41	2.63	0.44*	5.19	0.38**	7.50
	(0.73)		(1.37)		(2.13)		(2.75)	
AIT_CRSP_12M	0.42*	1.11	0.44*	3.01	0.45**	5.34	0.60**	18.32
	(1.32)		(1.77)		(2.47)		(2.88)	

Table 4: Out-of-Sample R^2 of the S&P 500 Equity Premium

This table reports the proportional reduction in mean squared forecast error (MSFE) at the *h*-month horizon (1, 3, 6, and 12 months) for a predictive regression forecast of the S&P 500 equity premium based on the predictor in the first column versus the prevailing mean benchmark forecast. We refer to Table 1 for variable definitions and descriptions. The out-of-sample period starts in January 2010 and ends in December 2018. Inference is drawn using the MSPE-adjusted t-statistic of Clark and West (2007). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) Predictor	(2) *h* = 1	(3) *h* = 3	(4) *h* = 6	(5) *h* = 12
AIT_SPX	1.91**	7.66***	11.66***	37.87***
AIT_NON_SPX	-0.02	-0.22	-4.55	-5.01
AIT_CRSP	0.61	1.66*	-3.29	10.31**
BM	-0.56	1.95	12.37**	-50.48**
CRPR	1.43*	0.45	1.04	-1.31
DE	-1.20	-7.55	-22.19	-31.04
DFR	-0.50	-8.05	-9.61	-2.81
DFY	0.66	0.14	-9.06	-23.39
DP	0.59**	3.19***	6.36***	4.34**
DY	1.52***	4.22***	6.94***	5.81**
EP	-2.65	-13.46	-33.37	-40.49
EQIS	-0.17	-7.88	-3.39	-18.24
ICC	1.57	5.46**	17.47***	33.28***
INFL	-0.85	-9.13	3.46***	1.26*
LRET	-8.97	-6.35	-3.02	-1.41
LTR	-0.98	-5.87	-1.37	-3.85
LTY	1.34**	8.30***	8.47***	28.42***
NTIS	-3.73	-13.07	-20.6	-0.73**
SII	-36.94	-191.62	-512.32	-575.47
SVAR	3.85***	1.54	0.50	-9.51
TBL	0.67	2.85*	14.80***	34.32***
TMS	-0.63	-2.91	0.74	9.16**

Table 5: Forecast Encompassing Tests for S&P 500 Equity Premium Forecasts

This table reports the results for the forecast encompassing test of Harvey et al. (1998). We report for each variable the regression coefficient λ of the regression
$r_{t:t+h} = (1-\lambda) \cdot \hat{r}^{i}_{t:t+h} + \lambda \cdot \hat{r}^{AIT\_SPX}_{t:t+h}$,
where $r_{t:t+h}$ denotes the equity premium of the S&P 500 over the period from t to $t+h$, with h denoting the forecast horizon (1, 3, 6, and 12 months), i.e., $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The variable $\hat{r}^{i}_{t:t+h}$ denotes the h months ahead predictive regression forecast for the equity premium of the S&P 500 from one of the predictors listed in the first column of the table. We refer to Table 1 for variable definitions and descriptions. The competing h months ahead predictive regression forecast for the equity premium of the S&P 500 from aggregate insider trading of S&P 500 insiders is denoted by $\hat{r}^{AIT\_SPX}_{t:t+h}$. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance for the null hypothesis that the weight λ assigned to the forecast from S&P 500 insiders equals zero against the alternative hypothesis that the weight of the forecast from aggregate insider trading of S&P 500 insiders is greater than zero. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2) h = 1	(3) h = 3	(4) h = 6	(5) h = 12
AIT_SPX	–	–	–	–
AIT_NON_SPX	1.00*	1.00**	1.00**	1.00**
AIT_CRSP	0.95*	1.00**	1.00**	1.00**
BM	0.88*	0.66*	0.50**	0.72
CRPR	0.54*	0.98**	0.77*	1.00**
DE	1.00**	1.00***	1.00**	1.00**
DFR	0.81*	1.00***	1.00**	1.00**
DFY	0.80	1.00**	1.00**	1.00**
DP	0.80*	0.80*	0.68**	1.00**
DY	0.59	0.74*	0.66**	1.00**
EP	1.00**	1.00***	1.00**	1.00**
EQIS	0.70**	1.00*	0.83**	1.00**
ICC	0.56	0.63	0.34	0.56*
INFL	0.94**	1.00***	0.76*	1.00**
LRET	1.00***	1.00***	0.94**	1.00**
LTR	0.86**	1.00***	0.92**	1.00**
LTY	0.56*	0.48	0.52	0.55*
NTIS	0.77**	0.74**	0.69**	0.73*
SII	1.00***	1.00***	1.00***	1.00**
SVAR	0.10	0.94*	0.87**	1.00**
TBL	0.80	0.86*	0.39	0.55*
TMS	1.00**	1.00**	0.81**	0.87**

Table 6: Predictive Regression Results for Market Return Components

This table reports predictive regression estimation results using
$y_{t+1} = \alpha_y + \beta_y \cdot AIT\_SPX_t + \varepsilon_{t+1}$ for t = 1, . . . , T - 1,
where y_{t+1} is either the estimated expected return (ER), the estimated cash flow news (CF), or the estimated discount rate news (DR) of the continuous return of the S&P 500. The estimates of β_y for the three components are denoted by $\beta_{\hat{E}_t}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ for ER, CF, and DR, respectively. Estimates of the three components of the continuous return on the S&P 500 base on the Campbell (1991) and Campbell and Ammer (1993) vector autoregressive (VAR) approach. AIT_SPX_t denotes the AIT of S&P 500 insiders at t. The first column of the table lists the endogenous variables of the VAR. The premium on the S&P 500 is denoted by r, the remaining variable abbreviations as well as their definitions and descriptions are listed in Table 1. We follow Rapach et al. (2016) and set the intercept term for cash flow and discount rate news to zero. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) VAR variables	(2) $\beta_{\hat{E}_t}$	(3) $\hat{\beta}_{CF}$	(4) $\hat{\beta}_{DR}$
r, DP	0.29***	0.26*	-0.12
	(5.593)	(1.489)	(-1.890)
r, DP + BM	0.20***	0.41**	-0.07
	(2.921)	(2.123)	(-0.674)
r, DP + CRPR	0.34***	0.28*	-0.06
	(4.538)	(1.532)	(-0.912)
r, DP + DE	0.22***	0.67***	0.21*
	(3.442)	(3.068)	(1.698)
r, DP + DFR	0.32***	0.26*	-0.11
	(5.158)	(1.442)	(-1.649)
r, DP + DFY	0.69***	0.27	0.28
	(8.912)	(1.088)	(1.312)
r, DP + DY	0.27***	0.26*	-0.15
	(4.093)	(1.462)	(-2.631)
r, DP + EP	0.22***	0.67***	0.21*
	(3.442)	(3.068)	(1.698)
r, DP + EQIS	0.29***	0.34**	-0.05
	(3.36)	(1.812)	(-0.493)
r, DP + ICC	0.36***	0.15	-0.17
	(7.037)	(0.97)	(-1.66)
r, DP + INFL	0.29***	0.22	-0.17
	(4.117)	(1.243)	(-2.228)
r, DP + LRET	0.25***	0.27*	-0.16
	(3.299)	(1.479)	(-3.048)
r, DP + LTR	0.29***	0.29*	-0.10
	(5.005)	(1.593)	(-1.653)
r, DP + LTY	0.48***	0.30	0.11
	(5.993)	(1.222)	(0.67)
r, DP + NTIS	0.27***	0.21*	-0.19
	(2.722)	(1.466)	(-1.029)
r, DP + SII	0.46***	0.13	-0.09
	(5.951)	(0.77)	(-0.534)
r, DP + SVAR	0.54***	0.12	-0.02
	(8.883)	(0.759)	(-0.174)
r, DP + TBL	0.35***	0.06	-0.28
	(7.313)	(0.323)	(-2.618)
r, DP + TMS	0.29***	0.30*	-0.09
	(5.141)	(1.659)	(-1.331)

Table 7: Univariate In-Sample Regression Results for International Markets – Single-country

Panel A shows the OLS estimate of β and R^2 statistic for the predictive single-country regression model,
$r_{t:t+h} = \alpha + \beta \cdot AIT_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where AIT_t denotes the aggregate insider trading at t of one of the six countries (indicated by their three-letter ISO code), i.e., Canada (CAN), France (FRA), Germany (GER), Great Britain (GBR), Italy (ITA), or the U.S. (USA), and $r_{t:t+h}$ denotes the equity premium of one of these countries for the forecast horizon of $h = 1, 3, 6,$ and 12 months. AIT (USA) refers to the AIT of S&P 500 insiders, *AIT_SPX*. Parentheses below parameter estimates report heteroskedasticity- and autocorrelation-robust standard errors up to lag length h. Significance is based on one-sided wild-bootstrapped p-values.
Panel B reports the OLS estimates of β and R^2 statistic for the predictive pooled regression model,
$r_{i,t:t+h} = \alpha_i + \beta \cdot AIT_{i,t} + \varepsilon_{i,t:t+h}$ for $t = 1, \ldots, T - h$,
with $r_{t:t+h}$ as the equity premium of countries i, α_i the fixed-effect for country i, and $AIT_{i,t}$ the aggregate insider metric of country i at t. β indicates the average forecasting power of *AIT* within these six countries. The regression coefficients are estimated over the period from January 2005 until December 2018. Squared brackets contain the estimator's 95% one-sided confidence levels using bias-corrected wild bootstrap. Table 1 provides variable abbreviations as well as their definitions and descriptions. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Panel A: Single-country univariate regressions								
AIT (CAN)	-0.18	0.23	-0.06	0.06	0.07	0.12	0.25	3.94
	(-0.49)		(-0.18)		(0.23)		(1.09)	
AIT (FRA)	-0.48	1.08	-0.39	1.89	-0.27	1.57	-0.04	0.05
	(-1.14)		(-0.96)		(-0.7)		(-0.13)	
AIT (GER)	-0.47	0.83	-0.49	2.33	-0.55	5.20	-0.44	6.54
	(-1.08)		(-1.19)		(-1.43)		(-1.75)	
AIT (GBR)	-0.04	0.01	-0.08	0.14	-0.06	0.12	0.01	0.01
	(-0.11)		(-0.22)		(-0.15)		(0.05)	
AIT (ITA)	-0.70	1.47	-0.65	3.60	-0.58	4.74	-0.43	5.03
	(-1.40)		(-1.34)		(-1.22)		(-1.46)	
AIT (USA)	0.68***	2.83	0.71***	8.00	0.70***	12.95	0.69*	24.10
	(2.80)		(3.81)		(3.67)		(2.14)	
Panel B: Pooled univariate regression								
AIT	-0.20	0.39	-0.16	0.91	-0.12	1.31	0.01	1.94
	[-0.49; 0.09]		[-0.36; 0.03]		[-0.26; 0.03]		[-0.09; 0.10]	

Table 8: Univariate In-Sample Regression Results for International Markets – Cross-country

This table shows the OLS estimate of β and R^2 statistic for the predictive cross-country pooled regression model $r_{i,t:t+h} = \alpha_i + \beta \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}$ for t = 1, . . . , T - h,
where $r_{i,t:t+h}$ comprises the equity premia of country i, i.e., Canada, France, Germany, Great Britain, Italy, and the U.S., while $AIT_{j,t}$ represents the aggregate insider transaction measure of country j at t of one of the six countries (indicated by their three-letter ISO code), i.e., Canada (CAN), France (FRA), Germany (GER), Great Britain (GBR), Italy (ITA), or the U.S. (USA). AIT (j=*USA*) refers to the AIT of S&P 500 insiders, *AIT_SPX*. β indicates the predictive content of country j's *AIT* for the equity premia in country i. The regression coefficients are estimated over the period from January 2005 until December 2018. Squared brackets contain the estimator's 95% one-sided confidence levels using bias-corrected wild bootstrap. Table 1 provides variable abbreviations as well as their definitions and descriptions. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	ß	R^2 (%)	ß	R^2 (%)	ß	R^2 (%)	ß	R^2 (%)
AIT (j=CAN)	-0.09	0.24	0.00	0.58	0.13**	1.39	0.31***	5.85
	[-0.40; 0.20]		[-0.19; 0.20]		[0.00; 0.26]		[0.22; 0.39]	
AIT (j=FRA)	-0.38	0.88	-0.30	1.71	-0.21	2.00	-0.02	1.95
	[-0.70; -0.07]		[-0.51; -0.10]		[-0.36; -0.06]		[-0.11; 0.07]	
AIT (j=GER)	-0.36	0.83	-0.35	2.09	-0.35	3.68	-0.23	4.20
	[-0.66; -0.08]		[-0.54; -0.16]		[-0.49; -0.21]		[-0.32; -0.15]	
AIT (j=GBR)	-0.20	0.40	-0.24	1.33	-0.21	2.01	-0.13	2.69
	[-0.53; 0.12]		[-0.48; -0.02]		[-0.39; -0.04]		[-0.24; -0.03]	
AIT (j=ITA)	-0.52	1.47	-0.45	3.16	-0.42	4.71	-0.24	4.38
	[-0.84; -0.21]		[-0.67; -0.25]		[-0.58; -0.25]		[-0.34; -0.15]	
AIT (j=USA)	0.51***	1.43	0.57***	4.65	0.59***	8.55	0.66***	19.81
	[0.25; 0.77]		[0.43; 0.72]		[0.49; 0.7]		[0.55; 0.76]	

Table 9: Pooled Multivariate In-Sample Regression Results for International Markets

Panel A reports the OLS estimates of β and R^2 statistic for the multivariate predictive fixed-effects regression model,

$r_{i,t:t+h} = \alpha_i + \sum_{j=1}^{N} \bar{\beta}_j \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}$ for $t = 1, \ldots, T - h$,

with N denoting the number of countries within the panel ($N = 6$). $\bar{\beta}_j = \beta_{i,j}$ is the slope homogeneity restriction, which quantifies the average impact of country j's AIT on international equity premia. $AIT_{j,t}$ represents the aggregate insider transaction measure of country j at t of one of the six countries (indicated by their three-letter ISO code), i.e., Canada (CAN), France (FRA), Germany (GER), Great Britain (GBR), Italy (ITA), or the U.S. (USA). AIT (j=USA) refers to the AIT of S&P 500 insiders, AIT_SPX.

Panel B adds the three-months interest rate ($BILL_i$) and the dividend yield (DY_i) of country i to this specification. We also include the lagged continuously compounded return of the S&P 500 (LRET). Their parameter estimates are also subject to the slope homogeneity restriction. Further variable abbreviations as well as their definitions and descriptions are listed in Table 1. The regression coefficients are estimated over the period from January 2005 until December 2018. Squared brackets contain the estimator's 95% one-sided confidence levels using bias-corrected wild bootstrap. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) Predictor	(2) h = 1	(3) h = 3	(4) h = 6	(5) h = 12
Panel A: No covariates				
AIT (j=CAN)	-0.89	-0.65	-0.13	0.34***
	[-1.58;-0.20]	[-1.07;-0.24]	[-0.44;0.17]	[0.17;0.51]
AIT (j=FRA)	0.28	0.22*	0.10	-0.04
	[-0.14;0.67]	[-0.02;0.46]	[-0.07;0.27]	[-0.15;0.07]
AIT (j=GER)	0.08	-0.24	-0.63	-0.89
	[-0.49;0.62]	[-0.54;0.05]	[-0.83;-0.43]	[-1.02;-0.75]
AIT (j=GBR)	-0.06	-0.13	-0.05	0.04
	[-0.47;0.35]	[-0.41;0.14]	[-0.25;0.15]	[-0.06;0.14]
AIT (j=ITA)	-0.84	-0.56	-0.31	-0.04
	[-1.5;-0.15]	[-0.95;-0.15]	[-0.58;-0.03]	[-0.19;0.12]
AIT (j=USA)	1.30***	1.27***	1.09***	0.91***
	[0.83;1.79]	[1;1.55]	[0.88;1.29]	[0.76;1.06]
Adj. R^2	4.17	12.36	20.75	39.01
Panel B: With covariates				
$BILL_i$ (-)	1.12***	0.99***	1.04***	0.93***
	[0.44;1.83]	[0.58;1.41]	[0.73;1.36]	[0.75;1.11]
DY_i	0.44	0.45**	0.57***	0.36***
	[-0.09;0.99]	[0.12;0.77]	[0.35;0.79]	[0.23;0.5]
LRET	0.49***	-0.01	-0.06	-0.12***
	[0.15;0.83]	[-0.22;0.19]	[-0.21;0.09]	[-0.19;-0.05]
AIT (j=CAN)	-1.06	-0.98	-0.54	0.01
	[-1.77;-0.36]	[-1.39;-0.57]	[-0.84;-0.24]	[-0.17;0.17]
AIT (j=FRA)	0.16	0.15	0.01	-0.07
	[-0.30;0.6]	[-0.12;0.42]	[-0.18;0.21]	[-0.19;0.06]
AIT (j=GER)	0.61*	0.25	-0.11	-0.41
	[-0.09;1.32]	[-0.13;0.63]	[-0.39;0.16]	[-0.58;-0.24]
AIT (j=GBR)	0.77**	0.53**	0.64***	0.64***
	[0.11;1.46]	[0.11;0.96]	[0.34;0.93]	[0.49;0.79]
AIT (j=ITA)	-1.51	-1.21	-1.04	-0.68
	[-2.37;-0.64]	[-1.72;-0.71]	[-1.39;-0.67]	[-0.88;-0.47]
AIT (j=USA)	0.49	0.70***	0.49***	0.43***
	[-0.15;1.11]	[0.35;1.05]	[0.24;0.74]	[0.27;0.58]
Adj. R^2	6.89	16.95	31.54	53.95

Table 10: Out-of-Sample R^2 of the Equity Premium for International Markets

Panel A reports the out-of-sample R² (R^2_{OOS}) obtained from a predictive single-country model
$r_{t:t+h} = \alpha + \beta \cdot AIT_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where AIT_t denotes the aggregate insider trading at t of one of the six countries (indicated by their three-letter ISO code), i.e., Canada (CAN), France (FRA), Germany (GER), Great Britain (GBR), Italy (ITA), or the U.S. (USA). AIT (USA) refers to the AIT of S&P 500 insiders, AIT_SPX. $r_{t:t+h}$ denotes the equity premium of one of these countries for the forecast horizon of $h = 1, 3, 6,$ and 12 months. The first column reports the predictive variable for the construction of the forecast. A positive value of R^2_{OOS} indicates a reduction in mean squared forecast error (MSFE) at the *h*-month horizon (1, 3, 6, and 12 months) for a predictive regression forecast of the respective countries' equity premium based on the predictor in the first column versus the prevailing mean benchmark forecast.
Panel B shows the out-of-sample R² (R^2_{OOS}) obtained from a from a predictive cross-country model
$r_{i,t:t+h} = \alpha_i + \beta \cdot AIT\_SPX_t + \varepsilon_{i,t:t+h}$ for $t = 1, \ldots, T - h$,
where $r_{i,t:t+h}$ comprises the equity premia of country *i*, i.e., Canada, France, Germany, Great Britain, Italy, and the U.S., while AIT_SPX_t represents the aggregate trading of S&P 500 insiders at *t*. The first column displays country *i*. A positive value of R^2_{OOS} indicates a reduction in MSFE at the *h*-month horizon (1, 3, 6, and 12 months) for a predictive regression forecast of country i's equity premium based on the AIT_SPX versus the prevailing mean benchmark forecast.
We refer to Table 1 for variable definitions and descriptions. The out-of-sample period starts in January 2010 and ends in December 2018. Inference is drawn using the MSPE-adjusted t-statistic of Clark and West (2007). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) Predictor	(2) *h* = 1	(3) *h* = 3	(4) *h* = 6	(5) *h* = 12
Panel A: Single-country				
AIT (CAN)	-2.04	-6.09	-7.57	4.84
AIT (FRA)	-2.90	-11.00	-19.69	-30.93
AIT (GER)	-2.36	-6.99	-10.71	-21.52
AIT (GBR)	-2.96	-6.87	-32.56	-174.49
AIT (ITA)	-1.22	-4.75	-7.17	-6.86
AIT (USA)	1.91**	7.66***	11.66***	37.87***

Country	*h* = 1	*h* = 3	*h* = 6	*h* = 12
Panel B: AIT_SPX, cross-country				
CAN	-1.01	1.42	0.54*	14.96***
FRA	0.30	3.12**	9.08***	34.71***
GER	-0.16	1.47	4.62**	28.71***
GBR	1.74*	7.28**	13.71**	41.67***
ITA	-0.50	-0.87	2.36	22.14***
USA	2.05**	7.67***	11.63***	36.71***

Table 11: Predictive Regression Results for International Market Return Components

This table reports predictive regression estimation results using
$y_{t+1} = \alpha_y + \beta_y \cdot AIT\_SPX_t + \varepsilon_{t+1}$ for t = 1, . . . , T - 1,
where y_{t+1} is either the estimated expected return (ER), the estimated cash flow news (CF), or the estimated discount rate news (DR) of the continuous return of the country-specific equity index of Canada, France, Germany, Great Britain, Italy, and the U.S. The estimates of β_y for the three components are denoted by $\beta_{\hat{E}_t}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ for ER, CF, and DR, respectively. Estimates of the three components of the continuous return on the country-specific index are based on the Campbell (1991) and Campbell and Ammer (1993) vector autoregressive (VAR) approach. AIT_SPX_t represents the aggregate trading of S&P 500 insiders. The first column of the table lists the endogenous variables of the VAR. The premium on the country-specific equity index is denoted by r. *BILL*, *BM*, *DE*, *DY*, and *EP* denote the domestic three-months interest rate, the domestic book to market ratio, the domestic dividend payout ratio, the domestic dividend yield and the domestic earnings price ratio of the respective MSCI country index in Canada, France, Germany, Great Britain, and Italy. In the U.S., we use the respective metrics as listed in Table 1. LRET refers to the lagged S&P 500 return. We follow Rapach et al. (2016) and set the intercept term for cash flow and discount rate news to zero. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) VAR variables	(2) $\beta_{\hat{E}_t}$	(3) $\hat{\beta}_{CF}$	(4) $\hat{\beta}_{DR}$
r, DP	0.11***	0.41***	0.01
	[0.07;0.15]	[0.12;0.71]	[-0.04;0.07]
r, DP + BILL	0.33***	0.16	-0.02
	[0.29;0.38]	[-0.09;0.40]	[-0.11;0.07]
r, DP + BM	0.19***	0.23**	-0.08
	[0.13;0.26]	[0.01;0.45]	[-0.25;0.08]
r, DP + DE	0.20***	0.42***	0.12**
	[0.16;0.25]	[0.14;0.71]	[0.03;0.20]
r, DP + DY	0.14***	0.39***	0.02
	[0.09;0.19]	[0.09;0.68]	[-0.04;0.07]
r, DP + EP	0.20***	0.42***	0.12***
	[0.16;0.25]	[0.14;0.71]	[0.03;0.20]
r, DP + LRET	0.14***	0.48***	0.11***
	[0.10;0.18]	[0.19;0.77]	[0.04;0.18]

Table 12: Correlation of Cash Flow News

This table reports the Pearson correlation coefficient of the estimated cash flow news, $\widehat{N}_{i,t+1}^{CF}$, between the six countries in our sample from the international market return decomposition analysis in Table 11.

(1) Country	(2) CAN	(3) GER	(4) FRA	(5) GBR	(6) ITA	(7) U.S.
CAN	1.00					
GER	0.63	1.00				
FRA	0.68	0.91	1.00			
GBR	0.74	0.77	0.83	1.00		
ITA	0.58	0.78	0.86	0.71	1.00	
USA	0.73	0.78	0.79	0.77	0.66	1.00

INTERNET APPENDIX

Figure A1: Time Series of Alternative Aggregate Insider Transaction Metrics

The graph shows the time series of *AIT_NON_SPX* (non S&P 500 insiders) and *AIT_CRSP* (CRSP insiders) in the U.S. over the period from January 2005 until December 2018.

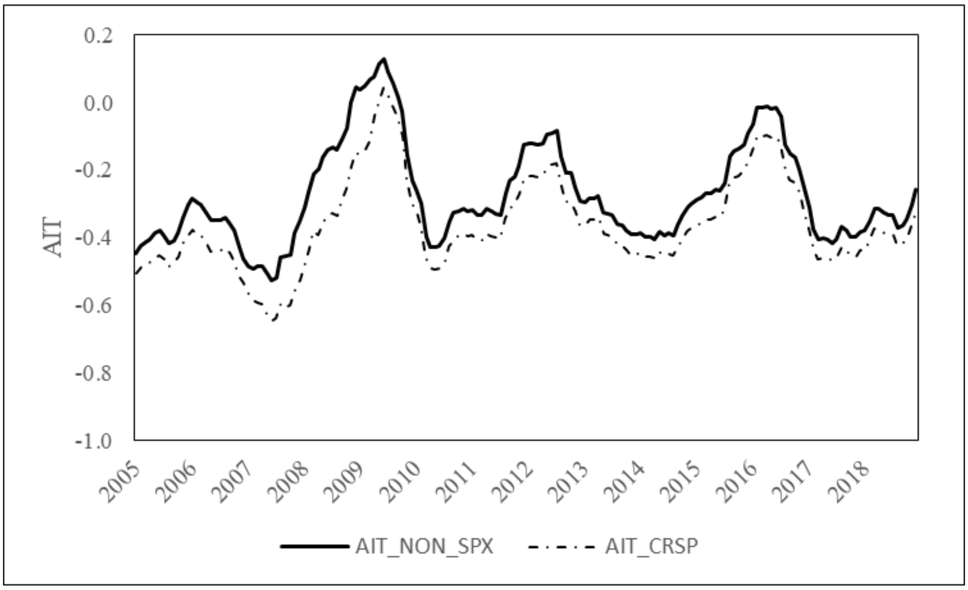

Figure A2: Time Series of Aggregate International Insider Transaction Metrics

The graph shows the time series of aggregate international insider transaction metrics over the period from January 2005 until December 2018.

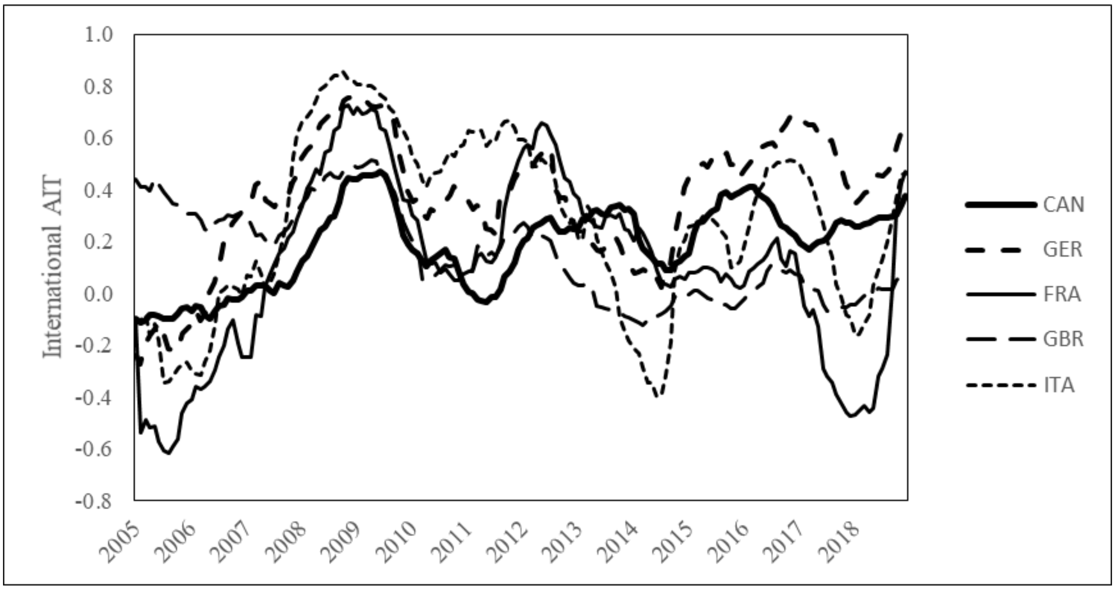

Table A1: Predictor variable correlations

This table reports correlation coefficients for the 22 predictor variables for our sample period January 2005 to December 2018. We refer to Table 1 for variable definitions and descriptions.

Variable	AIT_SPX	AIT_NON_SPX	AIT_CRSP	BM	CRPR	DE	DFR	DFY	DP	DY	EP	EQIS
AIT_SPX	1.00											
AIT_NON_SPX	0.71	1.00										
AIT_CRSP	0.82	0.97	1.00									
BM	-0.13	0.11	0.14	1.00								
CRPR	0.16	0.13	0.15	0.11	1.00							
DE	0.64	0.72	0.67	-0.18	0.10	1.00						
DFR	0.25	0.14	0.19	-0.06	0.22	0.18	1.00					
DFY	0.31	0.73	0.60	0.19	0.15	0.74	0.10	1.00				
DP	0.54	0.79	0.72	0.20	0.11	0.83	0.01	0.87	1.00			
DY	0.60	0.80	0.75	0.16	0.14	0.85	0.17	0.85	0.96	1.00		
EP	-0.62	-0.64	-0.60	0.29	-0.09	-0.98	-0.22	-0.64	-0.71	-0.76	1.00	
EQIS	0.16	0.29	0.23	-0.02	-0.09	0.26	0.03	0.33	0.35	0.29	-0.22	1.00
ICC	0.54	0.61	0.65	0.42	0.12	0.44	0.11	0.46	0.63	0.66	-0.35	0.45
INFL	-0.14	-0.14	-0.14	-0.11	-0.36	-0.09	-0.01	-0.25	-0.25	-0.23	0.03	-0.12
LAG	0.11	-0.05	0.02	-0.15	0.08	-0.02	0.51	-0.17	-0.26	0.04	-0.06	-0.22
LTR	-0.02	0.03	0.01	0.14	0.76	-0.03	-0.47	0.07	0.09	0.01	0.06	-0.10
LTY	-0.52	-0.31	-0.42	-0.22	-0.13	-0.01	-0.04	0.06	-0.20	-0.23	-0.05	0.12
NTIS	0.00	0.10	0.04	-0.04	0.01	0.10	-0.03	0.19	0.16	0.14	-0.08	0.13
SII	-0.34	0.05	-0.14	-0.04	-0.04	0.02	-0.20	0.26	0.16	0.12	0.02	0.32
SVAR	0.09	0.36	0.25	0.14	0.05	0.39	-0.25	0.66	0.61	0.48	-0.29	0.44
TBL	-0.54	-0.47	-0.56	-0.40	-0.09	-0.26	-0.10	-0.21	-0.47	-0.50	0.18	-0.32
TMS	0.40	0.51	0.52	0.38	0.11	0.41	0.07	0.41	0.57	0.59	-0.32	0.51

Table A1 continued

Variable	ICC	INFL	LAG	LTR	LTY	NTIS	SII	SVAR	TBL	TMS
ICC	1.00									
INFL	-0.16	1.00								
LAG	0.02	0.10	1.00							
LTR	0.04	-0.32	-0.26	1.00						
LTY	-0.38	0.20	-0.07	-0.09	1.00					
NTIS	0.07	0.01	-0.09	0.02	0.02	1.00				
SII	0.05	0.03	-0.13	0.10	0.37	0.23	1.00			
SVAR	0.28	-0.40	-0.49	0.21	0.10	0.16	0.25	1.00		
TBL	-0.88	0.15	-0.05	-0.02	0.68	-0.03	0.13	-0.12	1.00	
TMS	0.92	-0.13	-0.03	0.05	-0.27	0.08	0.11	0.32	-0.88	1.00

Table A2: In-Sample Regression Results for the CRSP Index Equity Premium

This table reports the OLS estimate of β and R^2 statistic for the predictive regression model,
$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where x_t denotes the predictive variable at t and $r_{t:t+h}$ denotes the equity premium of the CRSP index for the forecast horizon of $h = 1, 3, 6,$ and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The predictive variables in the first column are standardized to have a mean of zero and standard deviation of one; (-) imply that we take the negative of the respective predictor. We refer to Table 1 for variable definitions and descriptions. The regression coefficients are estimated over the period from January 2005 until December 2018. Parentheses below parameter estimates report heteroskedasticity- and autocorrelation-robust standard errors up to lag length h. Significance is based on wild-bootstrapped p-values and provided at the 1%, 5%, and 10% level (denoted by ***, **, and *).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
AIT_SPX	0.66***	2.45	0.71***	7.04	0.71***	11.81	0.71*	23.98
	(2.55)		(3.51)		(3.57)		(2.25)	
AIT_NON_SPX	0.14	0.11	0.16	0.36	0.20	0.91	0.43**	8.70
	(0.32)		(0.40)		(0.58)		(2.89)	
AIT_CRSP	0.43	1.04	0.45*	2.78	0.46**	4.97	0.63**	18.89
	(1.27)		(1.70)		(2.35)		(3.12)	
BM	0.40	0.91	0.61*	5.24	0.80**	14.88	0.68*	21.62
	(1.12)		(2.00)		(2.54)		(1.82)	
CRPR	0.96*	5.16	0.16	0.37	0.35*	2.81	0.18*	1.53
	(1.64)		(0.44)		(1.58)		(1.87)	
DE	0.21	0.24	0.33	1.50	0.39	3.49	0.32	4.96
	(0.38)		(0.81)		(1.37)		(2.47)	
DFR	0.60	2.04	0.30	1.23	0.33	2.52	0.20	1.83
	(0.90)		(0.78)		(1.34)		(1.49)	
DFY	-0.25	0.35	-0.01	0.00	0.24	1.36	0.32	4.96
	(-0.39)		(-0.02)		(0.67)		(2.09)	
DP	0.23	0.31	0.37	1.92	0.49	5.65	0.52**	12.80
	(0.37)		(0.70)		(1.55)		(4.29)	
DY	0.45	1.14	0.46	2.97	0.54	6.94	0.56**	14.62
	(0.81)		(1.06)		(2.15)		(4.40)	
EP	-0.19	0.19	-0.29	1.18	-0.32	2.47	-0.24	2.69
	(-0.37)		(-0.78)		(-1.11)		(-1.41)	
EQIS	-1.01	5.76	-0.70	6.87	-0.55	7.01	-0.11	0.59
	(-1.70)		(-1.59)		(-1.67)		(-0.62)	
ICC	0.47*	1.26	0.45*	2.78	0.52*	6.29	0.60*	17.23
	(1.41)		(1.54)		(2.17)		(2.48)	
INFL (-)	-0.35	0.68	-0.22	0.68	0.28	1.79	0.32**	4.92
	(-1.04)		(-0.56)		(1.12)		(1.83)	
LRET	0.68	2.60	0.27	0.98	0.13	0.37	0.06	0.20
	(1.37)		(0.76)		(0.65)		(0.44)	
LTR	0.47	1.22	-0.05	0.03	0.10	0.24	0.03	0.05
	(1.28)		(-0.18)		(0.77)		(0.39)	
LTY (-)	0.58**	1.87	0.54*	4.11	0.58*	7.95	0.50	11.94
	(1.96)		(1.90)		(1.85)		(1.73)	
NTIS (-)	-0.73	2.96	-0.75	7.96	-0.68	10.75	-0.45	9.65
	(-1.38)		(-1.49)		(-1.39)		(-1.17)	
SII (-)	0.73*	2.97	0.97*	13.04	1.04*	25.14	0.77	27.89
	(1.48)		(1.92)		(2.06)		(2.19)	
SVAR	-1.03	5.96	-0.58	4.69	-0.03	0.02	0.16	1.22
	(-1.99)		(-1.78)		(-0.13)		(1.52)	
TBL (-)	0.33*	0.61	0.34*	1.65	0.40*	3.77	0.54	13.61
	(1.31)		(1.57)		(1.79)		(1.82)	
TMS	0.08	0.04	0.06	0.05	0.15	0.51	0.39*	7.19
	(0.24)		(0.19)		(0.61)		(2.01)	

Table A3: In-Sample Regression Results for the Equally Weighted S&P 500 Equity Premium

This table reports the OLS estimate of β and R^2 statistic for the predictive regression model,
$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$ for $t = 1, \ldots, T - h$,
where x_t denotes the predictive variable at t and $r_{t:t+h}$ denotes the equity premium of the equally weighted S&P 500 for the forecast horizon of $h = 1, 3, 6,$ and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The predictive variables in the first column are standardized to have a mean of zero and standard deviation of one; (-) imply that we take the negative of the respective predictor. We refer to Table 1 for variable definitions and descriptions. The regression coefficients are estimated over the sample from January 2005 until December 2018. Parentheses below parameter estimates report heteroskedasticity- and autocorrelation-robust standard errors up to lag length h. Significance is based on wild-bootstrapped p-values and provided at the 1%, 5%, and 10% level (denoted by ***, **, and *).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
AIT_SPX	0.82***	3.02	0.88***	8.71	0.88***	14.26	0.84*	27.08
	(2.76)		(3.97)		(3.97)		(2.49)	
AIT_NON_SPX	0.32	0.45	0.35	1.35	0.39	2.83	0.61**	14.45
	(0.60)		(0.76)		(1.01)		(3.34)	
AIT_CRSP	0.62*	1.74	0.65**	4.72	0.66**	8.19	0.81**	25.07
	(1.56)		(2.18)		(2.87)		(3.42)	
BM	0.48	1.05	0.74**	6.17	0.94**	16.44	0.77*	22.76
	(1.23)		(2.08)		(2.57)		(1.87)	
CRPR	1.12*	5.70	0.15	0.26	0.41*	3.07	0.20**	1.52
	(1.72)		(0.35)		(1.70)		(1.95)	
DE	0.42	0.80	0.54	3.29	0.59	6.50	0.50*	9.40
	(0.62)		(1.19)		(1.91)		(3.12)	
DFR	0.58	1.53	0.35	1.36	0.37	2.50	0.22	1.78
	(0.72)		(0.81)		(1.34)		(1.51)	
DFY	-0.10	0.05	0.17	0.33	0.46	3.94	0.52	10.57
	(-0.13)		(0.27)		(1.18)		(3.19)	
DP	0.45	0.90	0.61	4.15	0.75	10.41	0.74**	21.09
	(0.57)		(0.99)		(2.18)		(5.47)	
DY	0.71	2.29	0.70	5.54	0.80*	11.87	0.77**	22.94
	(1.01)		(1.43)		(2.91)		(5.29)	
EP	-0.38	0.66	-0.48	2.60	-0.50	4.61	-0.38	5.59
	(-0.60)		(-1.13)		(-1.50)		(-1.85)	
EQIS	-1.10	5.50	-0.71	5.65	-0.50	4.7	-0.01	0.00
	(-1.59)		(-1.41)		(-1.42)		(-0.05)	
ICC	0.70**	2.23	0.66*	4.91	0.74**	10.23	0.80**	24.63
	(1.74)		(1.96)		(2.61)		(2.91)	
INFL (-)	-0.36	0.57	-0.25	0.70	0.39	2.82	0.38**	5.42
	(-0.97)		(-0.58)		(1.57)		(1.96)	
LRET	0.82*	3.03	0.25	0.70	0.09	0.14	0.03	0.03
	(1.44)		(0.63)		(0.43)		(0.16)	
LTR	0.63*	1.79	-0.09	0.10	0.13	0.32	0.04	0.06
	(1.55)		(-0.3)		(0.96)		(0.40)	
LTY (-)	0.65**	1.88	0.59**	3.98	0.64*	7.71	0.55	11.49
	(2.01)		(1.9)		(1.89)		(1.73)	
NTIS (-)	-0.77	2.70	-0.81	7.41	-0.70	8.98	-0.42	6.84
	(-1.29)		(-1.46)		(-1.31)		(-1.02)	
SII (-)	0.84*	3.15	1.12*	14.05	1.14*	24.34	0.79	23.81
	(1.52)		(2.09)		(2.13)		(2.13)	
SVAR	-1.06	5.02	-0.56	3.59	0.12	0.27	0.29	3.30
	(-1.62)		(-1.39)		(0.44)		(2.31)	
TBL (-)	0.48**	1.05	0.50**	2.85	0.57**	6.02	0.70*	18.56
	(1.74)		(2.00)		(2.14)		(2.15)	
TMS	0.26	0.30	0.23	0.61	0.35	2.23	0.59*	13.16
	(0.63)		(0.65)		(1.20)		(2.54)	

Table A4: Out-of-Sample R^2 of the CRSP Index Equity Premium

This table reports the out-of-sample R² (R^2_{OOS}) obtained from a model
$r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$,
where x_t denotes the predictive variable at t, $r_{t:t+h}$ denotes the equity premium of the CRSP index over the period from t to $t+h$, with h denoting the forecast horizon which equals 1, 3, 6, and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The first column reports the predictive variable for the construction of the forecast. We refer to Table 1 for variable definitions and descriptions. A positive value of R^2_{OOS} indicates that the predictor in the first column outperforms the historical mean. The out-of-sample period starts in January 2010 and ends in December 2018. Inference is drawn using the MSPE-adjusted t-statistic of Clark and West (2007). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2) h = 1	(3) h = 3	(4) h = 6	(5) h = 12
AIT_SPX	1.44*	6.63**	10.53***	40.75***
AIT_NON_SPX	-0.03	-0.12	-3.87	-2.58
AIT_CRSP	0.46	1.44	-3.25	12.05***
BM	-0.69	-0.12	1.55**	-84.59*
CRPR	1.06*	0.60	1.28	-1.94
DE	-1.28	-7.26	-20.67	-30.57
DFR	-0.56	-8.36	-9.19	-3.47
DFY	0.33	-0.51	-8.49	-21.92
DP	0.69**	3.94***	8.10***	8.51***
DY	1.78***	4.91***	8.72***	9.85***
EP	-2.91	-13.30	-32.13	-41.88
EQIS	-1.27	-10.80	-6.75	-21.91
ICC	1.31	4.87*	15.44**	29.06***
INFL	-0.61	-7.98	5.22***	-0.26
LAG	-11.09	-6.49	-2.90	-2.41
LTR	-1.50	-5.07	-0.53	-4.55
LTY	-0.04*	4.70***	-7.73***	10.24***
NTIS	-4.48	-16.00	-29.48	-11.96*
SII	-38.69	-198.89	-529.59	-618.19
SVAR	3.80**	0.45	-0.45	-10.45
TBL	0.21	1.15	9.38**	23.22***
TMS	-0.71	-3.11	-0.62	4.14*

Table A5: Out-of-Sample R^2 of the Equally Weighted S&P 500 Equity Premium

This table reports the out-of-sample R² (R^2_{OOS}) obtained from a model $r_{t:t+h} = \alpha + \beta \cdot x_t + \varepsilon_{t:t+h}$, where x_t denotes the predictive variable at t, $r_{t:t+h}$ denotes the equity premium of the equally weighted S&P 500 over the period from t to $t+h$, with h denoting the forecast horizon which equals 1, 3, 6, and 12 months, i.e. $r_{t:t+h} = (1/h) \cdot (r_{t+1} + r_{t+2} + \ldots + r_{t+h})$. The first column reports the predictive variable for the construction of the forecast. We refer to Table 1 for variable definitions and descriptions. A positive value of R^2_{OOS} indicates that the predictor in the first column outperforms the historical mean. The out-of-sample period starts in January 2010 and ends in December 2018. Inference is drawn using the MSPE-adjusted t-statistic of Clark and West (2007). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2) h = 1	(3) h = 3	(4) h = 6	(5) h = 12
AIT_SPX	1.14*	5.30**	5.30***	34.37***
AIT_NON_SPX	0.05	-0.48	-8.13	-8.93
AIT_CRSP	0.33	0.36*	-8.73	5.72***
BM	-0.15	-2.97	-7.38**	-100.49*
CRPR	1.06*	0.45	0.58	-2.49
DE	-2.41	-11.39	-29.96	-44.12
DFR	-0.56	-9.05	-8.96	-3.49
DFY	0.16	-1.75	-13.51	-29.87
DP	1.82***	6.74***	11.89***	11.54***
DY	2.70***	7.38***	12.37***	13.17***
EP	-4.90	-19.69	-44.99	-60.17
EQIS	-2.63	-12.18	-7.07	-14.64
ICC	2.17	8.20**	20.77**	41.44***
INFL	-0.52	-8.72	7.57***	-0.81
LAG	-14.59	-5.32	-1.49	-2.65
LTR	-1.95	-6.07	-0.03	-5.23
LTY	-1.28*	1.78***	-34.99***	-22.04***
NTIS	-3.24	-13.43	-20.85	-1.00*
SII	-46.03	-236.52	-580.65	-611.11
SVAR	3.74**	0.55	-2.32	-15.60
TBL	1.39*	4.97*	15.25**	32.53***
TMS	0.22	-0.21	4.32	17.63***

Table A6: Predictive Regression Results for Market Return Components – Non S&P 500 Insiders

This table reports predictive regression estimation results using
$y_{t+1} = \alpha_y + \beta_y \cdot AIT\_NON\_SPX_t + \varepsilon_{t+1}$ for t = 1, . . . , T - 1,
where y_{t+1} is either the estimated expected return (ER), the estimated cash flow news (CF), or the estimated discount rate news (DR) of the continuous return of the S&P 500. The estimates of β_y for the three components are denoted by $\beta_{\hat{E}_t}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ for ER, CF, and DR, respectively. Estimates of the three components of the continuous return on the S&P 500 base on the Campbell (1991) and Campbell and Ammer (1993) vector autoregressive (VAR) approach. $AIT\_NON\_SPX_t$ represents the aggregate trading of CRSP insiders that do not belong to a S&P 500 company at t. The first column of the table lists the endogenous variables of the VAR. The premium on the S&P 500 is denoted by r, the remaining variable abbreviations as well as their definitions and descriptions are listed in Table 1. We follow Rapach et al. (2016) and set the intercept term for cash flow and discount rate news to zero. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) VAR variables	(2) $\beta_{\hat{E}_t}$	(3) $\hat{\beta}_{CF}$	(4) $\hat{\beta}_{DR}$
r, DP	0.26***	-0.11	0.03
	(3.645)	(-0.37)	(0.258)
r, DP + BM	0.25***	-0.04	0.08
	(3.448)	(-0.149)	(0.402)
r, DP + CRPR	0.29***	-0.12	0.04
	(2.47)	(-0.37)	(0.35)
r, DP + DE	0.25***	0.02	0.14
	(3.822)	(0.061)	(1.306)
r, DP + DFR	0.27***	-0.11	0.04
	(3.551)	(-0.372)	(0.327)
r, DP + DFY	0.20	0.06	0.13
	(1.272)	(0.194)	(0.35)
r, DP + DY	0.26***	-0.11	0.02
	(3.044)	(-0.385)	(0.192)
r, DP + EP	0.25***	0.02	0.14
	(3.822)	(0.061)	(1.306)
r, DP + EQIS	0.23*	-0.08	0.02
	(1.632)	(-0.296)	(0.102)
r, DP + ICC	0.29***	-0.11	0.05
	(3.976)	(-0.444)	(0.32)
r, DP + INFL	0.29***	-0.12	0.04
	(2.91)	(-0.441)	(0.318)
r, DP + LRET	0.25***	-0.11	0.01
	(2.695)	(-0.36)	(0.108)
r, DP + LTR	0.26***	-0.11	0.02
	(2.79)	(-0.365)	(0.221)
r, DP + LTY	0.33***	-0.14	0.06
	(4.285)	(-0.337)	(0.285)
r, DP + NTIS	0.14	-0.06	-0.05
	(1.136)	(-0.303)	(-0.157)
r, DP + SII	0.30***	-0.08	0.09
	(2.798)	(-0.403)	(0.377)
r, DP + SVAR	0.38**	-0.13	0.11
	(2.033)	(-0.523)	(0.577)
r, DP + TBL	0.28***	-0.15	-0.01
	(4.132)	(-0.554)	(-0.045)
r, DP + TMS	0.26***	-0.10	0.03
	(3.432)	(-0.333)	(0.31)

Table A7: Predictive Regression Results for Market Return Components – CRSP Insiders

This table reports predictive regression estimation results using
$y_{t+1} = \alpha_y + \beta_y \cdot AIT\_CRSP_t + \varepsilon_{t+1}$ for t = 1, . . . , T - 1,
where y_{t+1} is either the estimated expected return (ER), the estimated cash flow news (CF), or the estimated discount rate news (DR) of the continuous return of the S&P 500. The estimates of β_y for the three components are denoted by $\beta_{\hat{E}_t}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ for ER, CF, and DR, respectively. Estimates of the three components of the continuous return on the S&P 500 base on the Campbell (1991) and Campbell and Ammer (1993) vector autoregressive (VAR) approach. AIT_CRSP_t represents the aggregate trading of CRSP insiders at t. The first column of the table lists the endogenous variables of the VAR. The premium on the S&P 500 is denoted by r, the remaining variable abbreviations as well as their definitions and descriptions are listed in Table 1. We follow Rapach et al. (2016) and set the intercept term for cash flow and discount rate news to zero. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1) VAR variables	(2) $\beta_{\hat{E}_t}$	(3) $\hat{\beta}_{CF}$	(4) $\hat{\beta}_{DR}$
r, DP	0.29***	0.10	-0.04
	(4.561)	(0.445)	(-0.419)
r, DP + BM	0.30***	0.21	0.09
	(4.643)	(0.911)	(0.572)
r, DP + CRPR	0.32***	0.10	0.00
	(3.501)	(0.397)	(-0.009)
r, DP + DE	0.27***	0.34	0.19*
	(4.466)	(1.103)	(1.764)
r, DP + DFR	0.30***	0.10	-0.02
	(4.379)	(0.423)	(-0.266)
r, DP + DFY	0.36***	0.22	0.16
	(2.854)	(0.893)	(0.542)
r, DP + DY	0.27***	0.09	-0.06
	(3.45)	(0.422)	(-0.739)
r, DP + EP	0.27***	0.34	0.19*
	(4.466)	(1.103)	(1.764)
r, DP + EQIS	0.28***	0.15	0.00
	(2.469)	(0.653)	(-0.009)
r, DP + ICC	0.35***	0.02	-0.05
	(5.846)	(0.125)	(-0.364)
r, DP + INFL	0.30***	0.08	-0.05
	(3.529)	(0.365)	(-0.456)
r, DP + LRET	0.25***	0.10	-0.07
	(2.857)	(0.453)	(-0.986)
r, DP + LTR	0.29***	0.11	-0.03
	(3.849)	(0.45)	(-0.396)
r, DP + LTY	0.42***	0.08	0.08
	(6.673)	(0.262)	(0.415)
r, DP + NTIS	0.26***	0.06	-0.10
	(2.518)	(0.359)	(-0.388)
r, DP + SII	0.41***	0.04	0.03
	(4.804)	(0.238)	(0.169)
r, DP + SVAR	0.48***	0.03	0.08
	(4.058)	(0.181)	(0.506)
r, DP + TBL	0.33***	-0.05	-0.15
	(6.01)	(-0.231)	(-1.331)
r, DP + TMS	0.28***	0.13	-0.02
	(4.095)	(0.578)	(-0.195)

Table A8: In-Sample Regression Results for International Markets

This table shows the OLS estimate of β and R^2 statistic for the predictive cross-country pooled regression model $r_{i,t:t+h} = \alpha_i + \beta \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}$ for $t = 1, \ldots, T - h$,
where $r_{i,t:t+h}$ comprises the equity premia of country i, i.e., Canada, France, Germany, Great Britain, Italy, and the U.S., while $AIT_{j,t}$ represents the aggregate insider transaction measure of country j at t of one of the six countries (indicated by their three-letter ISO code), i.e., Canada (CAN), France (FRA), Germany (GER), Great Britain (GBR), Italy (ITA), or the U.S. (USA). AIT (j=*USA*) refers to the AIT of S&P 500 insiders, *AIT_SPX*. β indicates the predictive content of country j's *AIT* for the equity premia in country i. Squared brackets contain the estimator's 95% one-sided confidence levels using bias-corrected wild bootstrap. Table 1 provides variable abbreviations. We use the information based on the respective MSCI country indices. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Panel A: Canada								
AIT_SPX	0.28	0.55	0.33*	1.72	0.34	3.04	0.40	10.50
	(1.09)		(1.63)		(1.78)		(1.79)	
AIT_NON_SPX	0.00	0.00	0.02	0.01	0.02	0.02	0.23	3.43
	(-0.01)		(0.06)		(0.07)		(1.67)	
AIT_CRSP	0.17	0.22	0.19	0.59	0.19	0.93	0.36*	8.39
	(0.57)		(0.76)		(0.92)		(2.34)	
AIT_CAN	-0.18	0.23	-0.06	0.06	0.07	0.12	0.25	3.94
	(-0.49)		(-0.18)		(0.23)		(1.09)	
BILL (-)	0.17	0.22	0.19	0.54	0.18	0.82	0.27	4.57
	(0.66)		(0.74)		(0.69)		(0.92)	
BM	0.31	0.70	0.54	4.56	0.67	11.83	0.58	21.56
	(0.87)		(1.52)		(1.81)		(1.83)	
DE	0.25	0.43	0.26	1.07	0.23	1.45	0.24	3.61
	(0.99)		(1.14)		(1.05)		(1.24)	
DP	-0.06	0.02	0.14	0.32	0.26	1.85	0.26	4.42
	(-0.18)		(0.48)		(0.87)		(0.87)	
DY	-0.02	0.00	0.16	0.42	0.27	1.95	0.26	4.53
	(-0.07)		(0.55)		(0.88)		(0.87)	
EP	-0.35	0.89	-0.24	0.86	-0.12	0.37	-0.12	1.00
	(-1.08)		(-0.75)		(-0.46)		(-0.68)	
LRET	0.76**	4.11	0.22	0.73	0.05	0.08	0.02	0.04
	(2.04)		(0.68)		(0.31)		(0.21)	

Table A8 continued

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Panel B: France								
AIT_SPX	0.56*	1.46	0.66**	5.36	0.69**	10.18	0.74	21.75
	(1.60)		(2.56)		(2.66)		(1.96)	
AIT_NON_SPX	0.07	0.02	0.12	0.18	0.21	0.90	0.45*	8.10
	(0.16)		(0.31)		(0.60)		(2.12)	
AIT_CRSP	0.37	0.65	0.42	2.20	0.48*	4.83	0.67*	17.4
	(0.96)		(1.41)		(1.94)		(2.46)	
AIT_FRA	-0.48	1.08	-0.39	1.89	-0.27	1.57	-0.04	0.05
	(-1.14)		(-0.96)		(-0.7)		(-0.13)	
BILL (-)	0.77**	2.75	0.88**	9.72	0.94**	18.74	0.88*	30.29
	(1.92)		(2.24)		(2.28)		(2.49)	
BM	0.50	1.16	0.61*	4.58	0.69**	10.08	0.69*	18.68
	(1.20)		(1.96)		(2.21)		(1.94)	
DE	0.32	0.47	0.32	1.30	0.35	2.62	0.34	4.49
	(0.93)		(1.11)		(1.12)		(0.97)	
DP	-0.08	0.03	0.04	0.02	0.18	0.71	0.32	4.04
	(-0.18)		(0.12)		(0.57)		(1.02)	
DY	-0.05	0.01	0.08	0.09	0.20	0.88	0.32	3.93
	(-0.11)		(0.23)		(0.64)		(1.00)	
EP	-0.44	0.91	-0.36	1.60	-0.29	1.78	-0.17	1.16
	(-1.09)		(-1.03)		(-0.98)		(-0.68)	
LRET	0.62*	1.80	0.25	0.75	0.16	0.54	0.04	0.06
	(1.50)		(0.76)		(0.94)		(0.27)	
Panel C: Germany								
AIT_SPX	0.34	0.42	0.46*	2.02	0.53*	4.80	0.68	15.47
	(0.94)		(1.61)		(1.88)		(1.80)	
AIT_NON_SPX	-0.05	0.01	-0.02	0.01	0.05	0.04	0.38	4.88
	(-0.1)		(-0.05)		(0.13)		(1.88)	
AIT_CRSP	0.23	0.20	0.27	0.70	0.33	1.84	0.61*	12.70
	(0.53)		(0.83)		(1.25)		(2.35)	
AIT_GER	-0.47	0.83	-0.49	2.33	-0.55	5.20	-0.44	6.54
	(-1.08)		(-1.19)		(-1.43)		(-1.75)	
BILL (-)	0.58*	1.25	0.71	4.87	0.77	10.24	0.74	18.55
	(1.29)		(1.46)		(1.46)		(1.60)	
BM	0.78*	2.26	0.90**	7.77	1.00***	17.21	0.88**	26.46
	(1.52)		(2.55)		(4.54)		(3.34)	
DE	0.11	0.05	0.18	0.31	0.36	2.16	0.48	7.71
	(0.23)		(0.63)		(1.43)		(1.56)	
DP	-0.08	0.02	0.06	0.03	0.24	0.97	0.44	6.49
	(-0.12)		(0.11)		(0.65)		(1.60)	
DY	-0.10	0.04	0.09	0.07	0.28	1.34	0.44	6.61
	(-0.16)		(0.17)		(0.8)		(1.57)	
EP	-0.20	0.15	-0.19	0.34	-0.28	1.31	-0.28	2.65
	(-0.53)		(-0.63)		(-0.99)		(-0.99)	
LRET	1.01**	3.75	0.35	1.16	0.15	0.41	0.11	0.39
	(2.26)		(0.98)		(0.79)		(0.66)	

Table A8 continued

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1		h = 3		h = 6		h = 12	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Panel D: Great Britain								
AIT_SPX	0.70**	3.46	0.73***	11.24	0.71***	18.25	0.65*	28.69
	(2.55)		(3.61)		(3.92)		(2.56)	
AIT_NON_SPX	0.30	0.64	0.32	2.22	0.37	5.08	0.54**	19.73
	(0.84)		(1.04)		(1.37)		(4.05)	
AIT_CRSP	0.54**	2.06	0.56**	6.59	0.57**	12.09	0.68***	31.18
	(1.82)		(2.44)		(3.22)		(4.00)	
AIT_GBR	-0.04	0.01	-0.08	0.14	-0.06	0.12	0.01	0.01
	(-0.11)		(-0.22)		(-0.15)		(0.05)	
BILL (-)	0.51**	1.85	0.56*	6.62	0.60*	13.22	0.57	21.86
	(1.62)		(1.91)		(1.87)		(1.83)	
BM	0.36	0.91	0.44*	4.05	0.52**	9.74	0.63*	26.54
	(1.20)		(1.80)		(2.19)		(2.51)	
DE	0.74***	3.81	0.65***	9.01	0.58**	12.25	0.43*	12.41
	(2.70)		(3.10)		(2.80)		(1.96)	
DP	0.14	0.14	0.18	0.67	0.29	3.01	0.39	10.30
	(0.42)		(0.61)		(1.15)		(1.85)	
DY	0.18	0.22	0.18	0.70	0.30	3.37	0.39	10.48
	(0.50)		(0.62)		(1.17)		(1.82)	
EP	-0.79	4.37	-0.68	9.90	-0.57	11.81	-0.37	9.15
	(-2.85)		(-3.12)		(-2.72)		(-1.76)	
LRET	0.30	0.61	0.06	0.08	0.07	0.17	-0.02	0.03
	(0.99)		(0.30)		(0.53)		(-0.21)	
Panel E: Italy								
AIT_SPX	0.49	0.71	0.53*	2.42	0.60*	5.08	0.78	16.34
	(1.22)		(1.69)		(1.88)		(1.74)	
AIT_NON_SPX	-0.16	0.08	-0.11	0.11	0.04	0.02	0.37	3.68
	(-0.28)		(-0.23)		(0.09)		(1.51)	
AIT_CRSP	0.16	0.08	0.20	0.34	0.32	1.43	0.60*	9.72
	(0.32)		(0.50)		(0.98)		(1.91)	
AIT_ITA	-0.70	1.47	-0.65	3.60	-0.58	4.74	-0.43	5.03
	(-1.40)		(-1.34)		(-1.22)		(-1.46)	
BILL (-)	0.85**	2.15	0.94**	7.60	0.99*	13.97	0.95*	23.87
	(1.99)		(2.16)		(2.06)		(2.31)	
BM	0.42	0.52	0.47	1.91	0.62	5.53	0.68	12.43
	(0.95)		(1.32)		(1.59)		(1.45)	
DE	0.56*	0.95	0.39	1.29	0.47	3.09	0.42	4.75
	(1.35)		(1.00)		(1.36)		(1.36)	
DP	-0.39	0.45	-0.27	0.63	-0.03	0.01	0.06	0.09
	(-0.52)		(-0.42)		(-0.05)		(0.17)	
DY	-0.27	0.22	-0.17	0.23	0.01	0.00	0.07	0.12
	(-0.38)		(-0.25)		(0.02)		(0.21)	
EP	-0.59	1.03	-0.40	1.39	-0.45	2.92	-0.40	4.28
	(-1.33)		(-0.98)		(-1.22)		(-1.25)	
LRET	0.89**	2.37	0.26	0.56	0.22	0.69	0.07	0.15
	(1.79)		(0.70)		(1.12)		(0.43)	

Table A9: Pooled Multivariate In-Sample Regression Results for International Markets (excluding the U.S. equity premium)

The table reports the OLS estimates of β and adjusted R^2 statistic for the multivariate predictive fixed-effects regression model,

$r_{i,t:t+h} = \alpha_i + \sum_{j=1}^{N} \bar{\beta}_j \cdot AIT_{j,t} + \varepsilon_{i,t:t+h}$ for t = 1, . . . , T - h,

with N denoting the number of countries within the panel ($N = 6$). $\bar{\beta}_j = \beta_{i,j}$ is the slope homogeneity restriction, which quantifies the average impact of country j's AIT on international equity premia. As a robustness exercise, we drop the U.S. equity premium from the panel. Further variable abbreviations as well as their definitions and descriptions are listed in Table 1. Squared brackets contain the estimator's 95% one-sided confidence levels using bias-corrected wild bootstrap. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2)	(3)	(4)	(5)
Predictor	h = 1	h = 3	h = 6	h = 12
AIT (j=CAN)	-0.87	-0.63	-0.10	0.36***
	[-1.69;-0.09]	[-1.10;-0.16]	[-0.44;0.24]	[0.17;0.55]
AIT (j=FRA)	0.27	0.21	0.09	-0.04
	[-0.19;0.71]	[-0.06;0.48]	[-0.11;0.29]	[-0.17;0.09]
AIT (j=GER)	0.12	-0.24	-0.65	-0.90
	[-0.49;0.74]	[-0.57;0.09]	[-0.87;-0.41]	[-1.05;-0.74]
AIT (j=GBR)	0.02	-0.06	0.03	0.11*
	[-0.47;0.50]	[-0.37;0.25]	[-0.19;0.25]	[0.00;0.21]
AIT (j=ITA)	-0.92	-0.60	-0.36	-0.10
	[-1.65;-0.18]	[-1.05;-0.15]	[-0.66;-0.05]	[-0.27;0.06]
AIT (j=USA)	1.27***	1.25***	1.08***	0.92***
	[0.73;1.84]	[0.94;1.56]	[0.84;1.31]	[0.75;1.10]
Adj. R^2	3.83	11.71	20.33	39.72

Table A10: Predictive Regression Results for International Market Return Components (excluding the U.S. equity premium)

This table reports predictive regression estimation results using
$y_{t+1} = \alpha_y + \beta_y \cdot AIT\_SPX_t + \varepsilon_{t+1}$ for $t = 1, \ldots, T - 1$,
where y_{t+1} is either the estimated expected return (ER), the estimated cash flow news (CF), or the estimated discount rate news (DR) of the continuous return of the country-specific equity index of Canada, France, Germany, Great Britain, Italy, and the U.S. As a robustness exercise, we drop the U.S. equity premium from the estimation. The estimates of β_y for the three components are denoted by $\beta_{\hat{E}_t}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ for ER, CF, and DR, respectively. Estimates of the three components of the continuous return on the country-specific index are based on the Campbell (1991) and Campbell and Ammer (1993) vector autoregressive (VAR) approach. The first column of the table lists the endogenous variables of the VAR. The premium on the country-specific equity index is denoted by r. *BILL*, *BM*, *DE*, *DY*, and *EP* denote the domestic three-months interest rate, the domestic book to market ratio, the domestic dividend payout ratio, the domestic dividend yield and the domestic earnings price ratio of the respective MSCI country index in Canada, France, Germany, Great Britain, and Italy. In the U.S., we use the respective metrics as listed in Table 1. LRET refers to the lagged S&P 500 return. We follow Rapach et al. (2016) and set the intercept term for cash flow and discount rate news to zero. The regression coefficients are estimated over the period from January 2005 until December 2018. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

(1)	(2)	(3)	(4)
VAR variables	$\beta_{\hat{E}_t}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$
r, DP	0.07***	0.44**	0.04*
	[0.03;0.11]	[0.10;0.79]	[-0.01;0.10]
r, DP + BILL	0.33***	0.18	0.03
	[0.28;0.38]	[-0.11;0.47]	[-0.06;0.13]
r, DP + BM	0.19***	0.20	-0.09
	[0.12;0.26]	[-0.06;0.45]	[-0.28;0.10]
r, DP + DE	0.20***	0.37**	0.10*
	[0.15;0.25]	[0.03;0.7]	[-0.01;0.20]
r, DP + DY	0.11***	0.41**	0.05*
	[0.06;0.17]	[0.07;0.75]	[-0.01;0.11]
r, DP + EP	0.20***	0.37**	0.10*
	[0.15;0.25]	[0.03;0.7]	[-0.01;0.20]
r, DP + LRET	0.12***	0.44**	0.09***
	[0.08;0.17]	[0.10;0.78]	[0.02;0.15]