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SNB Working Papers
14/2017

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SWISS NATIONAL BANK

Legal Issues

ISSN 1660-7716 (printed version)
ISSN 1660-7724 (online version)

Predicting returns on asset markets of a small, open economy and the influence of global risks*

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November 1, 2017

Abstract

Stylized facts of asset return predictability are mainly based on evidence from the US, a large, closed economy, and, hence, are not necessarily representative of small, open economies. Furthermore, discount-rate news mainly drive US asset returns. This is not the case in other economies. We use Switzerland as example to highlight the importance of these issues and to assess the impact of global risks on the predictability of asset returns of a small, open economy. We find that

*The paper benefited from comments and suggestions by Tjeerd Boonman and Adrien Verdelhan. We are also grateful to two anonymous referees of the SNB working paper series, Richard Stehle and participants at the SSES Annual Meeting 2017 (Lausanne), the EEFS Annual Conference 2017 (Ljubljana) and the SNB Brown Bag workshop for comments on earlier versions of this paper that circulated under the title "What Goliaths and Davids among Swiss firms tell us about expected asset returns and the state of the economy". Moreover, we gratefully acknowledge that David Rapach made his MATLAB code for various tests of stock return predictability publicly available. We also thank Christian Grisse for providing us with his MATLAB code to test for gradual time variation in parameter estimates. Any errors and omissions are our own. The views, opinions, findings, and conclusions or recommendations expressed in this paper are strictly those of the authors. They do not necessarily reflect the views of the Swiss National Bank. The Swiss National Bank does not take responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper.

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the forecast ability of the best Swiss predictive variable varies over time. This time variation is linked to global foreign currency risks.

JEL: E32, F31, G15, G17

KEYWORDS: bond market, business cycle, foreign exchange rate, predictability, risk premium, stock market

1 Introduction

This paper assesses the forecast ability of predictors of US bond and stock returns in a different country-specific context. Such international assessments help shed light on the issue of whether conclusions drawn from empirical studies based on US data apply to other economies as well. For example, Cochrane (2008) shows that the US dividend-price ratio predicts US stock market returns but does not forecast dividends. However, international evidence provided by Engsted and Pedersen (2010) and Rangvid et al. (2014) suggests that dividend-price ratios predict dividend growth in a number of countries.

Swiss asset markets provide an ideal test case for this research question for three reasons. First, Rey (2004) and Nitschka (2014) highlight that the time variation in excess returns on both Swiss stock and Swiss bond markets predominantly reflects cash-flow news, i.e., dividend news in the case of stock market returns and long-term inflation news in the case of government bond returns. In this respect, Swiss stock markets appear to be representative of other European stock markets (Nitschka, 2010). By contrast, time variation in the returns on US stock and bond markets is primarily driven by discount-rate/expected-return news (Campbell, 1991; Campbell and Ammer, 1993; Campbell and Vuolteenaho, 2004). We confirm these earlier studies in this paper. Second, the US is a large, closed economy, whereas Switzerland is small and open. According to OECD trade statistics, exports and imports comprised approximately 13% and 15% of the annual US GDP in 2015, respectively. The corresponding numbers for Switzerland were 63% (exports) and 51% (imports) respectively. Hence, global risks have more potential to influence the Swiss economy, its asset markets and, thus, the expected returns on Swiss asset markets. Third, we have access to data at the individual stock level for all stocks that have ever been electronically traded on the Swiss stock exchange. This information allows us to construct high quality Swiss versions of recently proposed predictors that rely on broad measures of cash-flows in their construction. To the best of our knowledge, our stock-level data is extraordinarily detailed compared with stock market data of other small, open economies.

Our empirical assessments over the sample period from January 1999 to August 2016 show that these differences between the US and Switzerland matter, even though we find similarities. For example, changes in large firms' stock market capitalization relative to changes in the aggregate stock market capitalization - "Goliath versus David" or GVD - forecast Swiss stock market returns at time horizons of six to twelve months in- and out-of-sample. This finding corroborates the US evidence of this variable's forecast power (Duarte and Kapadia, 2015). While other popular predictor variables exhibit in-sample forecast ability for Swiss stock returns as well, they tend to perform poorly in out-of-sample tests (Goyal and Welch, 2008).

Where do differences between the US and Switzerland show up? And how do they affect the assessment of asset return predictability? We find three major differences.

First, the distinction between the two components of GVD matters for its ability to forecast Swiss stock market returns. This is not the case in the US. [1] GVD^{new} (differences in net new equity issuances between large firms and the aggregate market) dominates variation in Swiss GVD. It is this component that exhibits the in-sample predictive power for Swiss stock market returns and for returns' cash-flow news. GVD^{old} (differences in the returns on existing capital between large firms and the aggregate market) does not forecast stock market returns because it predicts Swiss stock market

[1] Slegers (2014) examined the forcast ability of GVD (and its components) for France, Germany, Italy and UK but did not find any sign of predictive ability. However, Slegers (2014) has to employ a short-cut to calculate GVD^{new}. By contrast, we have high quality and detailed information about the data that is necessary to compute GVD^{new}. This difference in the data quality is the most likely explanation of the differences in our assessments of GVD's forecast performance, because results in Nitschka (2010) suggest that the stock markets of Germany but also France and Italy are primarily driven by cash-flow news and thus similar to the Swiss stock market that we examine.

returns' discount-rate news. Compared with cash-flow news, discount-rate news is not an important driver of Swiss stock market returns. However, only GVD, i.e., the combination of GVD^{new} with GVD^{old}, exhibits out-of-sample predictive power. None of the two GVD components alone forecasts Swiss stock market returns out-of-sample.

Second, statistical tests show that the forecast ability of GVD, particularly that of GVD^{old}, varies over time. Because Switzerland is a small, open economy, we assess whether global risks play a role in this respect. To empirically approximate global risks, we use the international CAPM proposed by Brusa et al. (2014) as the benchmark, because it features a global stock market factor and two factors reflecting risks on foreign exchange markets. Because Swiss franc exchange rates (and thus Swiss franc denominated assets) are typically considered a "safe haven" for global investors (e.g., Ranaldo and Söderlind, 2010; Grisse and Nitschka, 2015), this model feature makes it particularly appealing in the context of this paper. Indeed, our results show that the time variation in the forecast ability of GVD^{old} is a function of two global foreign currency risk factors (carry and global dollar) proposed by Lustig et al. (2011) and Verdelhan (2015). Without the influence of global foreign exchange market risks, GVD^{old} would significantly predict future stock market returns in-sample. The predictive power of GVD^{old} seems to depend heavily on the global dollar factor.

Third, we find that returns on Swiss government bond indexes are hardly predictable at all. Neither GVD nor the other predictors exhibit both in- and out-of-sample predictive power for Swiss bond returns. This observation stands in contrast to US evidence, where GVD predicts stock and bond returns in- and out-of-sample (Duarte and Kapadia, 2015). This difference might be explained by the fact that long-term inflation news is the main driver of variation in Swiss bond returns. All of the predictor variables under study are supposed to capture time-varying expected risk premia over the business cycle but not necessarily long-term inflation expectations. In addition, Swiss stock returns (or the underlying revenues of firms) are highly dependent on shocks originating abroad. As a result, adverse shocks abroad tend to lead to falling Swiss stock prices. By contrast, Swiss government bonds are typically considered to be "safe havens" for investors. Their prices tend to rise when adverse shocks materialize abroad.

To summarize, our evaluation of asset return predictability shows that country-specific features of asset markets and the exposure to global risks matter. Global foreign exchange rate risks seem to have an important effect on the predictability of returns on asset markets of small, open economies. Hence, it cannot be taken for granted that evidence of asset return predictability based on US data is applicable to the rest of the world.

The remainder of the paper is organized as follows. Section 2 provides an update of earlier studies that decompose US and Swiss stock and bond market returns into cash-flow and discount-rate news driven components. Section 3 describes the data and their sources. Section 4 presents the baseline empirical results. Section 5 takes a closer look at the best predictor of Swiss stock returns and section 6 assesses the influence of global risks on the predictability of Swiss asset returns. Finally, section 7 concludes. The appendix provides additional results and robustness checks.

2 Characterizing US and Swiss asset return dynamics

This paper assesses the capability of different variables to forecast Swiss asset returns. These variables have already proven their predictive power for US asset returns. However, we argue that it cannot be taken for granted that the US evidence is representative of a small, open economy such as Switzerland. One reason is that global risks have potentially more influence on small, open economies than on large, closed ones. Moreover, the main drivers of US and other economies' asset returns are different (Nitschka, 2010). This section illustrates this point using Switzerland as an example.

To characterize the dynamics of US and Swiss asset returns, we build on fundamental insights from the Campbell and Shiller (1988) log-linear approximation of the present value model, which links stock prices, stock returns and dividends. This framework is applicable to bond returns as well (Shiller and Beltratti, 1992; Campbell and Ammer, 1993). In a nutshell, these present value models show that any variation in asset returns reflects revisions in expectations, i.e. news, about future cash-flows (NCF), future real interest rates (NRR), future risk premia (NRX) or a combination of the three.

Following Campbell (1991), news about future stock returns (NR) obey

$$NR = NCF - NRR - NRX \tag{1}$$

while Campbell and Ammer (1993) highlight that bond return news (NBR) follow

$$NBR = -NBCF - NBRR - NBRX \tag{2}$$

Empirically, these news components can be obtained from a simple vector autoregressive model (Campbell, 1991; Campbell and Ammer, 1993)

$$z_{t+1} = \mathit{\Gamma} z_t + u_{t+1} \tag{3}$$

where z is the vector of variables that enter the vector autoregressive system (VAR). $\mathit{\Gamma}$ denotes the VAR coefficients and the error terms are represented by u. In the case of stock returns, news of stock market returns, news of real interest rates and news about future risk premia can be directly estimated from the VAR. Cash-flow news is the residual. By contrast, in the case of bond returns, news about risk premia is obtained as residual, while all of the other news components can be backed out from the VAR estimates (Campbell, 1991; Campbell and Ammer, 1993).

Nitschka (2014) uses this VAR framework to compare the asset return dynamics in Switzerland with the US using the same VAR system, i.e., the same variables enter the respective econometrician's information set [2]over the sample period from January 1975 to July 2013. The main results show that US stock and bond market returns are predominantly driven by news about risk premia/discount rates while cash-flow news is a main driver of Swiss stock and bond markets.

We repeat the VAR estimations of Nitschka (2014) for an extended sample period that ends in August 2016. Backing out the different stock and bond return news components from the estimated VARs for the US and Switzerland allows us to highlight the relative importance of the different news components for the total variation of stock and bond market returns. Because the news components can be correlated, the variance decomposition (here for stock returns) has the following form

$$\begin{aligned} var(NR) = {} & var((NCF) + var(NRR) + var(NRX) \\ & - 2cov(NCF, NRR) - 2cov(NCF, NRX) + 2cov(NRR, NRX) \end{aligned} \tag{4}$$

Table (1) presents the results from the decomposition of the variance in unexpected Swiss and US asset returns in equation (4). These statistics are normalized by the variance of the total stock market return news such that they sum to one. In addition, the table gives the 95% confidence interval of the statistics in parentheses below the variance shares, after 1000 bootstrap draws. The left panel depicts the results for the decomposition of stock return news. The right panel of table (1) delivers the corresponding results for bond market returns.

The main results corroborate Nitschka (2014). Stock return news in Switzerland is dominated by cash-flow news. By contrast, variation in US

[2]The VAR systems feature the excess return on the respective stock market as its first element. The second element is the short-term (here one month) real interest rate. The real rate was obtained using realized, monthly inflation based on a consumer price index. Then follow the change in the short-term rate, the term spread (ten-year government bond yield minus short-term rate) and the dividend-price ratio.

stock market returns appears to be driven by cash-flow and risk premium news to roughly the same extent. The differences between Switzerland and the US are even more pronounced when we look at the variance decomposition of unexpected bond return variation. Swiss bond returns are mainly driven by cash-flow news (long-term inflation news) while US bond return variation primarily reflects news about risk premia.

[about here Table (1)]

Hence, variables that proved their forecast capability for US stock and bond market returns do not necessarily predict returns on Swiss stock and bond markets as well. The time series dynamics of asset returns in the US and Switzerland have different main drivers.

3 Asset return predictability: data and descriptive statistics

This paper assesses the predictability of Swiss asset returns over the sample period January 1999 to August 2016. This sample period is restricted by the availability of data to construct some of the potential predictors. The appendix provides more details on this issue. Unless otherwise noted, we work with monthly data.

3.1 Dependent variables

This paper examines whether excess returns on Swiss stock and bond market indices as well as GDP growth are predictable. Excess returns are defined as log return on the Swiss stock or bond index, $r_{t+1} = ln(\frac{P_{t+1}}{P_t})$, in excess of the risk-free rate, which we approximate by the one-month Swiss franc (CHF) Libor rate. The source of the Libor rate is the Swiss National Bank (SNB).

As a proxy of the Swiss stock market index, we use the MSCI Swiss total return index denominated in CHF. Total return indices assume that dividends are reinvested in the index. MSCI indices are widely used in academic studies and are publicly available on the MSCI website.

As a proxy of the Swiss bond market index, we use the Citigroup World Bond Index Switzerland which is constructed under the assumption that coupon payments are reinvested in the index. In addition, it aggregates bonds across maturities. The source of this data is Datastream.

Our source of quarterly real, calendar and seasonality adjusted GDP is the Swiss State Secretariat of Economic Affairs SECO.

3.2 Predictors of asset returns

The choice of potential explanatory variables for future asset returns is limited by the availability of data to construct some of these predictors. We focus on four, by now standard, predictors of stock returns. Moreover, we compile a Swiss version of a recently proposed predictor of US stock returns, bond returns and GDP that we describe in detail.

3.2.1 Standard predictors

The first standard predictor is the log price-earnings ratio, pe (Graham and Dodd, 1934; Campbell and Shiller, 1988; Shiller, 2000). We use current price-earnings ratios and the level of the Swiss Market Index (SMI) to compute an adjusted price-earnings ratio of the Swiss stock market, i.e., the log of current Swiss stock prices minus the log of a 10-year moving average of earnings. The source of these data is the SIX exchange.

The second standard predictor is the term spread defined as the spread between the Swiss ten-year government bond yield and the 1M Libor (ts). The data source is the SNB. The choice of this predictor is based on Hjalmarsson (2010), who argues that indicators constructed from interest rate data are the most robust predictors of stock market returns across a large cross-section of national stock markets.

The third standard predictor is the log dividend-price ratio of the Swiss stock market, dp (Fama and French, 1988). We compile the log dividend-price ratio as the log of the sum of monthly dividends over the past year minus the log of this month's MSCI Swiss price index. To be consistent with the use of the MSCI indices, we compile the dividends from the difference between the returns on the MSCI total return index and the returns on the MSCI price index for Switzerland.

Finally, we follow Boudoukh et al. (2007) and compute a net payout yield of the Swiss stock market (py). The net payout yield is defined as the sum of dividends and share buybacks minus the issuance of new equity from $t - \Delta t$ to t and normalized by the aggregate stock market capitalization in t. We set Δt to 12 months. The data source is the SNB [3]

3.2.2 GVD ("Goliath versus David")

Using stock-level data on the information about different components of changes in a stock's market capitalization, we compile a Swiss version of a recently proposed predictor of US asset returns and the state of the economy (Duarte and Kapadia, 2015).

Duarte and Kapadia (2015) argue that changes in large firms' stock market capitalization relative to the changes in the aggregate stock market capitalization ("Goliath versus David", or GVD) are a natural candidate as a predictor of asset returns. When the market capitalization of small firms falls relative to the market capitalization of the big firms, i.e. GVD increases, then this movement signals a bad economic state. This interpretation is based on work by Bernanke and Gertler (1989), Gertler and Gilchrist (1994) and Kiyotaki and Moore (1997). They argue that small firms are more sensitive to the business cycle. Moreover, there is evidence that small US firms'

[3] https://data.snb.ch/en/topics/finma#!/cube/capmovshare

stocks exhibit greater variation in expected returns than large firms' stocks during expansions and recessions (Perez-Quiros and Timmermann, 2000). In addition, changes in the market capitalization of large firms in the form of issuances of new equity might be less sensitive to the business cycle than equity issuances of small firms. Covas and Den Haan (2011) find equity issuances of small firms to be more pro-cyclical than equity issuances of large firms in a sample of US firms.

We follow Duarte and Kapadia (2015) and define GVD as change in the weight of the L largest firms in the aggregate Swiss stock market from $t - \Delta t$ to t. Hence, GVD basically measures the total return of the L largest firms relative to the total return on the market portfolio. This return difference can be decomposed into components that reflect the relative returns on existing capital, i.e., the relative ex-dividend returns ($R^{ex}_{t,\Delta t}$), and the relative growth rates due to the raising of (net) new capital ($NNC_{t,\Delta t}$)

$$GVD^{L}_{t,\Delta t} = (R^{ex,L}_{t,\Delta t} - R^{ex,M}_{t,\Delta t}) + (NNC^{L}_{t,\Delta t} - NNC^{M}_{t,\Delta t}) \tag{5}$$

The first term on the right-hand side of equation (5), $(R^{ex,L}_{t,\Delta t} - R^{ex,M}_{t,\Delta t})$, measures the changes in the prices of existing capital of the L largest firms relative to the M firms that form the market portfolio. The second term on the right-hand side of equation (5), $(NNC^{L}_{t,\Delta t} - NNC^{M}_{t,\Delta t})$, measures changes in the market capitalisation of the L largest firms due to capital raising or capital decreasing activities relative to the M firms that form the market portfolio.

NNC reflects the difference between corporate actions that increase and decrease market capitalization. Measures that increase the market capitalization are the issuance of new shares or new listings. Measures that decrease market capitalization are delistings of firms or share buybacks and dividend payments.

As in Duarte and Kapadia (2015), we use the following abbreviations $GVD^{L,old}_{t,\Delta t} = (R^{ex,L}_{t,\Delta t} - R^{ex,M}_{t,\Delta t})$ and $GVD^{L,new}_{t,\Delta t} = (NNC^{L}_{t,\Delta t} - NNC^{M}_{t,\Delta t})$, such that

$$GVD^{L}_{t,\Delta t} = GVD^{L,old}_{t,\Delta t} + GVD^{L,new}_{t,\Delta t} \tag{6}$$

Our main empirical results are obtained for $L = 50$. We also follow Duarte and Kapadia (2015) and set Δt to 12 months in the baseline specification of GVD. The appendix provides additional information about the Swiss stock market (basically M and its variation over time) and results obtained with other definitions of GVD (varying L).

3.3 Descriptive statistics

3.3.1 Dependent variables

As table (2) shows, average excess returns on the Swiss stock market were lower than the corresponding excess returns on the Swiss government bond index over our sample period of January 1999 to August 2016. The average Swiss stock market excess return was approximately one percentage point p.a., whereas the Swiss government bond yielded an excess return of more than 2.5% p.a.

Furthermore, the stock market returns were more volatile than the bond returns. According to the sample t–statistics of the mean excess returns, returns on the Swiss stock market were not significantly different from zero, which stands in contrast to the bond market evidence. Consequently, the Sharpe ratio of the Swiss stock market return is close to zero, while the corresponding statistic for the bond market return is approximately 0.2. The pairwise correlation between the two excess return series is negative with a correlation coefficient of roughly -0.3.

These descriptive statistics reflect the fact that most of the sample period was dominated by crisis periods (global financial crisis, euro area sovereign debt crisis) which heavily affected Swiss asset markets. During these periods demand for Swiss government bonds was particularly high and supply was limited[4], such that yields on Swiss government bonds up to maturities of more than 10 years temporarily fell into negative territory. By contrast, Swiss firms listed on the stock market are to a large extent linked to international financial conditions. Revenues of the 20 largest firms originate mostly from abroad (Rasch, 2015). Hence, crises abroad had a pronounced impact on Swiss stock market risk premia.

[about here Table (2)]

3.3.2 Predictors of asset returns

Panel A of table (3) presents descriptive statistics of the potential predictors of Swiss asset returns. Most importantly, all of the predictors have high autocorrelation coefficients. Combined with our small sample size, these high autocorrelations make the Stambaugh (1999) bias a pertinent issue. We correct for this bias in our predictive regressions.

In addition, Panel B of table (3) shows that the predictors under study are in some cases highly correlated with each other. For example, the absolute values of the pairwise correlation coefficients between the dividend-price ratio, the price-earnings ratio and the payout yield are close to 0.8. This is not surprising because these variables are ratios of different measures of aggregate cash-flows with aggregate prices. The term spread and GVD are less strongly correlated with the other predictors.

[about here Table (3)]

[4] At the end of 2016, the nominal value of all outstanding Swiss Federal government debt amounted to about CHF 76bn ($\approx 12\%$ of annual 2015 GDP).

4 Predicting stock and bond market returns: baseline results

This section presents our baseline results. We start with the results from our assessments of in-sample predictability of Swiss stock and bond market returns. The second subsection provides the corresponding out-of-sample forecast results, while the third subsection evaluates whether the forecast ability of the predictors varies over time.

4.1 In-sample predictability

Our in-sample predictability assessments are based on OLS regressions of log returns measured from t to $t + h$ in excess of the risk-free rate on the predictive variables presented in section 3.2. The regression has the following form

$$r_{t,t+h}^{stock,bond} = \alpha + \beta^h x_t + \varepsilon_{t,t+h} \tag{7}$$

in which the log excess return for time horizon $t + h$ is the sum of log one-period excess returns from t to $t + h$ and x denotes one of the predictors. The forecast horizons, h, that we consider are one month, three months, six months and twelve months.

The combination of long-horizon regressions over a relatively short sample period from January 1999 to August 2016 with overlapping returns and predictors that exhibit high autocorrelations leads to a number of well-known econometric issues that will affect the inference from this regression (Ang and Bekaert, 2007; Boudoukh et al., 2008; Ferson et al., 2003; Hodrick, 1992; Stambaugh, 1999). To mitigate these issues, we use a wild bootstrap to compute test statistics. We follow Rapach et al. (2016) and compute heteroskedasticity and autocorrelation robust t-statistics from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h > 0$, because the regressors are defined in such a way that high values predict high excess returns.[5] We therefore look at $-pe$ instead of pe. This one-sided test procedure follows the recommendation by Inoue and Kilian (2005). Following Rapach et al. (2016) we standardize all predictors to have a standard deviation of one to assess the relative importance of the different predictors. The p-values of the t-statistics were obtained after 1000 bootstrap draws. Varying the number of draws from 1000 to 10000 has no material impact on the test statistics.

The results from the in-sample forecast regression in equation (7) for excess returns on the Swiss stock market are summarized in table (4). Only the price-earnings ratio and GVD exhibit in-sample predictive power for Swiss stock market returns. The price-earnings ratio statistically significantly predicts stock returns at all forecast horizons from one to twelve months with R^2 statistics ranging from 2% to 15%. GVD exhibits almost equal predictive power for the horizons from three to twelve months with R^2 statistics varying between 0.5% (one-month horizon) and 13% (12-month horizon). At the one-month ahead forecast horizon, the price-earnings ratio exhibits the largest estimate of $\hat{\beta}$. At the longer forecast horizons, the $\hat{\beta}$ estimates of both the price-earnings ratio and GVD are approximately 0.6, i.e., a one standard deviation increase in one of these variables is associated with a roughly seven percentage point increase in annual Swiss stock market returns. The other variables do not reveal any in-sample forecast ability for Swiss stock returns.

[about here Table (4)]

The picture changes quite a bit when we regard the Swiss government bond market. Table (5) presents these results. Swiss bond excess returns are difficult to predict even in in-sample regressions. Only the term spread exhibits statistically significant predictive power at the 95% confidence level. This finding pertains to the one-month ahead forecast horizon. We find some predictability by the price-earnings ratio as well. However, the estimated $\hat{\beta}$

[5]We are grateful to David Rapach for making the MATLAB code for these tests available on his website.

of the price-earnings ratio in these bond return regressions are only significant at the 90% confidence level for the one-month and three-month forecast horizons. With the exception of the term spread and the price-earnings ratio, none of the other variables shows any sign of forecast ability for Swiss bond excess returns. The main reason for this finding could be that variation in Swiss bond excess returns is primarily driven by cash-flow news, i.e., long-term inflation news (cf. Section 2). The predictor variables under study are not necessarily good proxies of changes in long-term inflation expectations.

[about here Table (5)]

4.2 Out-of-sample predictability

Goyal and Welch (2008) argue that a predictor of asset returns should not only display in-sample predictive power but should also forecast asset returns out-of-sample. Many of the standard predictors of US asset returns fail that test. There are notable exceptions. Short interest, loosely understood as an aggregate of the number of shares held short, explains future US stock market returns significantly both in in-sample and out-of-sample forecast regressions (Rapach et al., 2016). The US version of GVD forecasts both stock market returns and bond market returns as well as variables that proxy the state of the economy in-sample and out-of-sample (Duarte and Kapadia, 2015).

This section provides the results from assessments of the out-of-sample forecast ability of the Swiss versions of GVD and the predictors for stock market returns and bond market returns. We therefore run the regression in equation (7) over an evaluation period to obtain forecasts of the h-period ahead stock and bond market returns from the estimates of α and β for each of the predictor variables, i.e.,

$$\hat{r}_{t,t+h}^{stock,bond} = \hat{\alpha} + \hat{\beta}^h x_t \tag{8}$$

Then we compute the out-of-sample R^2 statistic (R^2_{oos}) proposed by Campbell and Thompson (2008). This statistic obeys

$$R^2_{oos} = 1 - \frac{\sum_{t=tOOS}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=tOOS}^{T}(r_t - \bar{r}_t)^2} \tag{9}$$

in which $\hat{r}$ is the predicted value of the excess returns from equation (8) and $\bar{r}_t$ is the historical mean of the respective return from the beginning of the sample until $T-1$. Following Rapach et al. (2016), we test the statistical significance of R^2_{oos} using the Clark and West (2007) test. A positive R^2_{oos} indicates that the mean squared forecast error from the predictions by one of the forecast variables under study is lower than predictions using only the historical mean return. We evaluate the out-of-sample predictive ability of the predictors for the forecast period starting in January 2008 ($tOOS$), i.e., the evaluation period for the forecasts runs from January 1999 to December 2007. Then we expand the window monthly from $tOOS$ to T.

Table (6) presents the results. Panel A gives the stock market evidence. Similar to the US evidence, the R^2_{oos} statistics suggest that GVD exhibits out-of-sample predictive power. At the six-month and twelve-month forecast horizons, the R^2_{oos} for out-of-sample forecasts using GVD are positive at approximately 6% and are significantly different from the benchmark model. The other forecast variables do not show any sign of out-of-sample forecast ability.

As panel B of table (6) highlights, the evidence of out-of-sample predictability of Swiss bond market returns is even weaker. Although the R^2_{oos} statistic for the price-earnings ratio is positive, it is not significantly different from the benchmark model. All of the other predictors produce forecasts that lead to negative R^2_{oos} statistics. In sum, Swiss bond market returns are hardly predictable at all.

[about here table (6)]

These findings help put the in-sample results into perspective. Only GVD confirms the in-sample forecast regression results. It is the only variable that clears the hurdle set by Goyal and Welch (2008). However, in contrast to the US evidence, the Swiss version of GVD does not forecast both stock and bond returns.

4.3 Is the predictive power stable over time?

One of the reasons to focus on Switzerland, a small, open economy, is the potential impact of global risks on Swiss asset markets and, thus, the predictability of Swiss asset returns.

Against this background, we cannot rule out that the predictive ability of the predictors under study varies over time due to the potential impact of global forces on the predictors or expected returns. For example, Rey (2013) and Miranda-Aggripino and Rey (2015) provide evidence of a global financial cycle, i.e., common movement in international capital flows, financial intermediaries' balance sheets and risky asset prices. This global financial cycle could affect the stability of the forecast ability of the predictors under study. Time variation in forecast ability might then explain why the evidence of predictability is basically limited to stock market returns and just one variable that clears the hurdle of predicting stock returns in- and out-of-sample.

To assess the stability of coefficients in the predictive regressions for stock and bond returns, we follow Grisse and Nitschka (2015) and Rapach et al. (2016) and use the test developed by Elliot and Müller (2006) to formally test for gradual time variation in β^h estimated in the in-sample regressions of equation (7). The main advantage of this test is that it does not force us to make specific assumptions about the statistical process for time variation that is considered in the alternative hypothesis. The null hypothesis is stability of the coefficient. We reject the null if the test statistic is more negative than the critical values. Table (7) gives the critical values at different significance levels of the null hypothesis and the test statistics from predictive regressions of stock (panel A) and bond (panel B) returns for all predictors and at all four forecast horizons.

The main test results are easily summarized. The predictive ability of GVD for stock returns varies over time. We reject the null of stability of the GVD regression coefficient at all forecast horizons. This finding does not apply to any of the other predictors of stock returns. In addition, the test results suggest that the regression coefficients in the predictive regressions for bond market returns are stable over time.

Hence, rather than explaining why we find relatively little forecast ability of most of the predictors under study, the test results presented in table (7) confront us with another puzzle. The forecast ability of the best predictor of stock returns, GVD, varies over time. Despite this time variation, it predicts stock returns in- and out-of-sample. We address this issue in the subsequent sections.

[about here table (7)]

5 A closer look at GVD

So far, the empirical results have shown that GVD predicts Swiss stock market returns in- and out-of-sample. At the same time, GVD exhibits no forecasting power for bond returns, which stands in marked contrast to the US evidence. Moreover, we find that the forecast ability of GVD varies over time. This section aims at shedding some light on these issues.

5.1 GVD and its components

We start with a variance decomposition of GVD to assess the relative importance of its two components GVD^{new} and GVD^{old}. In our baseline specification, GVD^{old} measures the changes in the prices of existing capital of the 50 largest firms relative to the aggregate market from $t-12$ to t. GVD^{new} measures changes in the market capitalisation of the 50 largest firms relative to the aggregate market from $t-12$ to t due to capital raising or capital decreasing activities such as the issuance of new shares or share buy-backs.

To get a sense of the main driver of the variation in total GVD, we perform a variance decomposition of the following form

$$var(GVD) = var(GVD^{old}) + var(GVD^{new}) + 2cov(GVD^{old}, GVD^{new}) \quad (10)$$

and

$$1 = \frac{var(GVD^{old})}{var(GVD)} + \frac{var(GVD^{new})}{var(GVD)} + 2\frac{cov(GVD^{old}, GVD^{new})}{var(GVD)} \quad (11)$$

The results of this decomposition are displayed in table (8) and clearly show that approximately 80% of the variation in GVD is driven by GVD^{new}, i.e., changes in net new capital of large firms relative to changes in net new capital of the total Swiss stock market. The differences in the relative valuation of large and small firms in the Swiss stock market are hence primarily driven by differences in net new capital between large firms and the aggregate market. The correlation between the two components of GVD, GVD^{new} and GVD^{old}, is negative but close to zero (correlation coefficient: -0.05).

[about here table (8)]

5.2 The components of GVD and the predictability of stock and bond returns

The variance decomposition in the previous subsection leaves the impression that the predictive ability of GVD for stock returns most likely reflects the forecast power of GVD^{new} . To evaluate this hypothesis, we repeat the in- and out-of-sample predictive regressions from sections 4.1 and 4.2 for each of the two GVD components. We also standardize the two components such that they have standard deviations of one.

The in-sample results summarized in table (9) confirm the intuition that the forecast ability of GVD for the Swiss stock market return is due to the forecast ability of GVD^{new}. Its point estimates displayed in panel A of table (9) are comparable with those estimated for GVD. The R^2 statistics are also similar ranging from 1% to 11%. By contrast, GVD^{old}, does not predict stock returns in-sample. Panel B shows that the decomposition of GVD into its two components does not lead to predictability of Swiss bond returns. None of the point estimates for GVD^{new} and GVD^{old} are significantly different from zero. The R^2 statistics remain close to zero as well.

[about here Table (9)]

Does GVD^{new}also account for the out-of-sample predictive power of GVD for stock returns? The results of the out-of-sample forecasts presented in table (10) suggest that this is not the case. None of the two GVD components exhibits out-of-sample forecast power. The out-of-sample R^2 statistics are mostly negative.

This finding suggests that we need the combination of GVD^{new} and GVD^{old} to forecast Swiss stock returns out-of-sample. This observation is similar to the US evidence of Duarte and Kapadia (2015) in the sense that GVD outperforms each of its two components.

The two components of the Swiss version of GVD are virtually uncorrelated with each other and thus seem to capture different information about future stock returns. We assess this question in the next subsection.

[about here Table (10)]

5.3 Predictability of cash-flow or discount-rate news?

We have highlighted in section 2 that cash-flow news (dividends in the case of stock returns, long-term inflation news in the case of bond returns) are the main drivers of Swiss asset returns. This observation stands in contrast to the corresponding US evidence.

Against this background, we expect that the predictive power of GVD for stock market returns reflects its forecast ability for the stock market returns' cash-flow news. We evaluate this hypothesis by a regression of the cash-flow news and discount-rate (risk premium)-driven components of stock and bond market returns on GVD. This approach is similar to the assessment of the drivers of the predictive power of short interest for US stock market returns by Rapach et al. (2016).

Moreover, based on the results presented in sections 5.1 and 5.2, we assess the predictive power of the components of GVD for the two news components of Swiss asset returns. We expect that GVD^{new} predicts the stock market returns' cash-flow news component because it is this component that explains the in-sample predictive power of GVD. In addition, we know from section 5.2 that only the combination of GVD^{new} and GVD^{old}, the two are basically uncorrelated with each other, is needed to predict stock returns out-of-sample. We assess whether this additional information from GVD^{old} is systematically related to one of the two asset return news components.

The OLS regressions take the following form

$$y_{t,t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \tag{12}$$

in which x represents GVD or one of its two components and $y = NCF$,NRX, $NBCF$ or $NBRX$ obtained from the VAR analysis in section 2 . Table (11) presents the results from these regressions.

The upper left panel of table (11) shows that indeed GVD forecasts the stock market return's cash-flow news driven component. Furthermore, it is GVD^{new} that is responsible for this finding. GVD^{old} does not predict cash-flow news.

This picture changes when we look at the results presented in the lower left panel of table (11). Neither GVD nor GVD^{new} significantly predict the stock market return's discount-rate news driven component. However, GVD^{old} does. This finding suggests that the out-of-sample predictive power of GVD for Swiss stock market returns requires information about both cash-flow and discount-rate news. GVD^{new} delivers the cash-flow news information while GVD^{old} provides information about discount-rate news.

The right panel of table (11) highlights that bond market returns are hardly predictable at all. The decomposition of the bond market return into its cash-flow and discount-rate news driven components does not provide further information on this issue.

[about here Table (11)]

5.4 Predictability of the state of the economy?

Basic asset pricing theory tells us that expected returns vary with the business cycle (e.g., Cochrane, 2005). Hence, predictors of asset returns should also be able to forecast changes in variables that reflect the state of the economy (Fama and French, 1989).

GVD predicts changes in measures of the state of the US economy (Duarte and Kapadia, 2015). This section assesses whether this finding pertains to the Swiss version of GVD or one of its components as well. It is thus an indirect test of whether the Swiss stock market return's cash-flow or discount-rate news can be associated with the state of the Swiss economy.

Duarte and Kapadia (2015) argue that the predictive power of GVD in the US reflects time-varying discount rates. Increases in GVD signal bad economic states, which means that it positively forecasts measures of risk premia on asset markets, such as excess returns on a stock index, and at the same time should negatively forecast measures of the state of the economy.

Against this background, we expect GVD^{old} to forecast changes in Swiss GDP because this component of GVD is related to discount-rate news. The relation of GVD^{new} to future GDP growth is unclear.

To assess this question, we run in-sample regressions of GDP growth on quarterly GVD or one of its components, i.e.,

$$\Delta gdp_{t,t+h} \quad = \quad \alpha + \beta^h x_t + \varepsilon_{t+1} \tag{13}$$

in which $\Delta gdp_{t,t+h}$ denotes the sum of quarterly changes of log real, calendar and seasonality adjusted Swiss GDP from quarter t to quarter $t+h$.

Against the background of the US evidence and the general motivation for the use of GVD, we expect to see negative β coefficients in the regression presented in equation (13). In analogue to the asset return regressions, we use a one-sided test and test $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h < 0$. The point estimates and the corresponding t-statistics are summarized in table (12). The p-values of the t-statistics are again obtained from a wild bootstrap procedure.

We observe only one significant and correctly, i.e., negatively, signed estimate of $\hat{\beta}^h$ in table (12). GVD^{old} indicates lower GDP growth one-quarter ahead. Its coefficient at the one-quarter forecast horizon is statistically significantly different from zero and is negatively signed. The R^2 statistic reaches nearly 5%. Beyond the one quarter horizon, however, it does not display any predictive power for GDP growth.

The regression coefficients for GVD^{new} have the wrong, i.e., positive, sign but are statistically zero. GVD^{new} does not show forecast ability for GDP growth, which explains why GVD, dominated by GVD^{new}, does not do so either.

These results are broadly in line with the US evidence, in the sense that the GVD component that reflects discount-rate news also predicts the state of the economy.

[about here Table (12)]

5.5 Is the predictive power of GVD components stable over time?

Table (7) has shown that the forecast ability of GVD varies over time. We apply the same test to the two components of GVD as well. Table (13) presents the results. The test results suggest that the regression coefficients of GVD^{old} in the stock return regressions vary over time. This time variation is most pronounced at the short forecast horizons from one month to six months. This finding partly applies to GVD^{new} as well. There is some evidence of gradual time variation in its regression coefficients. By contrast, we do not find any sign that the regression coefficients of $GVD^{old}$and GVD^{new} in the bond return regressions vary over time.

[about here Table (13)]

6 The impact of global risks on asset return predictability

Global risks could have an effect on the predictability of the asset returns of small, open economies. We view time variation in forecast regression coefficients as an indirect effect of global risks on the predictability of Swiss stock market returns. The first subsection evaluates the importance of this aspect of global risks.

In addition, global risk factors could directly forecast Swiss stock market returns or have close contemporaneous links with the predictors under study. This issue is the focus of the second subsection.

6.1 Time variation in the forecast ability of GVD and global risks

The forecast ability of GVD and its components varies over time according to the statistical test by Elliot and Müller (2006), presented in tables (7) and (13). This evidence suggests that the (in-sample) regression in equation (7) has to be rewritten as

$$r^{stock}_{t,t+h} = \alpha + \beta(t)x_t + \varepsilon_{t,t+h} \tag{14}$$

in which the regression coefficient β varies over time and x denotes GVD or one of its two components.

This section assesses whether we find conditioning variables to parameterize the time-varying regression coefficient. We assume that the OLS coefficient in the predictive regressions on GVD, or its components, is a linear function of the conditioning variable (Harvey, 1991; Ferson and Harvey, 1993; Dumas and Solnik, 1995), i.e.,

$$\beta(t) = \beta^0 + \beta^z z_t \tag{15}$$

in which z denotes a conditioning variable or a vector of conditioning variables. Plugging (15) into (14) then gives the predictive regression at the centre of this section

$$r^{stock}_{t,t+h} = \alpha + \beta^0 x_t + \beta^z(z_t x_t) + \varepsilon_{t,t+h} \tag{16}$$

What drives time variation in the regression coefficients β and, hence, the forecast ability of GVD or its components for Swiss stock market returns? Switzerland is a small, open economy and at the same time a financial centre. Global risks hence have the potential to materially affect the real economy as well as its financial markets. Furthermore, Swiss franc exchange rates or Swiss franc denominated assets are typically considered “safe havens” for investors. Evidence suggests that this characteristic is particularly pronounced during global stress periods (Ranaldo and Söderlind, 2010; Grisse and Nitschka, 2015). Against this background, we search for global factors as conditional variables in regression (16).

The three global factors proposed by Brusa et al. (2014) seem to be natural candidates to empirically assess the direct and indirect effects of global risks on Swiss stock markets.

The basic idea of the Brusa et al. (2014) version of the international CAPM is that a world stock market return (global CAPM) essentially captures all of the information about global shocks necessary to explain cross-country variation in stock market returns. However, when purchasing power parity does not hold, risk on foreign exchange markets matters (international CAPM).

In theory, the exchange rate risk in the intertemporal CAPM is represented by all bilateral exchange rates of the world. However, all bilateral exchange rates cannot be part of an empirical implementation of the international CAPM. Hence, early empirical versions of the international CAPM focus on the two or three most important bilateral exchange rates (Dumas and Solnik, 1995) to proxy exchange rate risk. Recently, Lustig et al. (2011) and Verdelhan (2015) have shown that this issue can be circumvented. They show that two risk factors capture all information about global shocks on foreign exchange markets, i.e., the shocks that matter in order to capture exchange rate risk in the international CAPM. Brusa et al. (2014) and this paper exploit these insights.

The Brusa et al. (2014) empirical version of the international CAPM features the return on a world stock market index as its first risk factor. The country indices that comprise the world stock market index are measured in local currency. The second risk factor is the carry factor introduced by Lustig et al. (2011). The carry factor is the return difference between foreign currency portfolios consisting of high interest rate and low interest rate currencies. The third risk factor in Brusa et al. (2014) is the dollar factor, i.e., the average currency return on all US dollar exchange rates. Here we depart from the Brusa et al. (2014) model. We are interested in the impact of global risk on the predictability of Swiss stock market returns. Hence, we use insights from Verdelhan (2015) and compute the global component of the dollar factor in order to work with two truly global foreign currency risk factors, i.e., foreign currency risk factors that are independent of the base currency. The global dollar factor is the return difference between foreign currency portfolios consisting of currencies with high and low exposures to the dollar factor. We provide details on the construction of our versions of the carry factor and the global dollar factor in the appendix.

Our assessment of the indirect effects of global risks focuses on time variation in the regression coefficients of the two components of GVD. The statistical tests have shown that time variation is most pronounced for GVD^{old}. In addition, GVD^{old} and GVD^{new} predict different parts of Swiss stock market returns (GVD^{new}: cash-flow news; GVD^{old}: discount-rate news).

Since the two components ,GVD^{old} and GVD^{new}, are almost uncorrelated with each other, we look at the vector of predictive variables, $x = [GVD^{old}, GVD^{new}]'$, and let $z = [world, carry, dollar^{global}]'$ be the vector of variables that potentially explain time variation in the regression coefficients of GVD^{old} and GVD^{new}. Standardizing the variables in z ($w = 1 + \frac{world_t}{\sigma(world)}$, with σ representing the standard deviation) to allow for comparison between the interaction terms and the uninteracted terms and plugging into equation (16) yields

$$
\begin{aligned}
r^{stock}_{t,t+h} = \alpha &+ \beta^h_{old} GVD^{old}_t + \beta^h_{new} GVD^{new}_t \\
&+\gamma^h_{old}(w_t GVD^{old}_t) + \gamma^h_{new}(w_t GVD^{new}_t) \\
&+\delta^h_{old}(c_t GVD^{old}_t) + \delta^h_{new}(c_t GVD^{new}_t) \\
&+\zeta^h_{old}(d_t GVD^{old}_t) + \zeta^h_{new}(d_t GVD^{new}_t) \\
&+\varepsilon_{t,t+h} \qquad (17)
\end{aligned}
$$

where c and d represent the standardized carry and global dollar factor. The results from regression (17) are summarized in table (14).

The left panel of the table gives the estimates of the β coefficients from regression (17). GVD^{new} exhibits predictive power for Swiss stock market returns at all forecast horizons. The regression coefficients are all positive and statistically significantly different from zero. This finding reflects that GVD^{new} predicts the component of the Swiss stock market return that is driven by cash-flow news. Cash-flow news is the main driver of variation in Swiss stock market returns as shown in section 2. Interestingly, GVD^{old}, the predictor of discount rate news, also exhibits some predictive power for stock market returns at the six month forecast horizon. In addition, the regression coefficient has the expected positive sign in the three-month- to twelve-month-ahead regressions. Why did this evidence not show up in section 5.2 when we ran predictive regressions of stock and bond market returns on the two GVD components?

The interaction terms of the two GVD components with the global foreign exchange risk factor help us understand why GVD^{old} did not exhibit predictive power in the regressions presented in section 5.2. The interaction of GVD^{old} with carry seems to have increased the sensitivity of future Swiss stock market returns to GVD^{old} at the short forecast horizons. The interaction of GVD^{old} with the dollar factor had the opposite effect. The interaction terms with the carry factor for the one-month- and three-month-ahead forecast regressions are positive and statistically significant. By contrast, the interaction term of GVD^{old} with the global dollar factor always significantly decreases the sensitivity of future stock market returns to GVD^{old}. The impact of the global dollar factor seems to be sufficient to make the overall sensitivity of future stock returns to GVD^{old} insignificant.

We also observe a significant, negative interaction term between GVD^{new} and the carry factor at the twelve-month forecast horizons. However, in contrast to the evidence for GVD^{old}, the impact of this global foreign exchange rate factor is insufficient to eliminate the predictive power of GVD^{new} for future stock market returns. The global dollar factor has no significant influence on the forecast ability of GVD^{new}.

The interaction terms of GVD^{new} and GVD^{old} with the world stock market return are not statistically different from zero. There is no link between time variation in the coefficient from the predictive regressions and the world stock market return.

Taken together, the results presented in this subsection suggest that the evidence of time-varying predictive power of GVD for Swiss stock market returns reflects the impact of global foreign exchange rate risk. In addition, our results show that the two global foreign exchange rate risk factors can have opposing effects on the ability of predictors to forecast stock market returns. This finding underscores that global dollar and the carry factor capture different dimensions of global foreign currency risks (Verdelhan, 2015).

[about here Table (14)]

6.2 Global risks and stock return predictability

The previous section aimed at assessing whether the presence of global risk factors leads to time variation in the predictive power of the two GVD components. However, the influence of global risks on the predictability of Swiss stock market returns could be more general than that. Global risks could have direct effects on the predictability of Swiss stock market returns through two channels. First, the global risk factors could directly predict Swiss stock returns. Second, GVD or its components, could be contemporaneously correlated with the risk factors.

We assess the first point by running the regression

$$r_{t,t+h}^{stock} = \alpha + \beta^h world_t + \gamma^h carry_t + \delta^h dollar_t^{global} + \varepsilon_{t,t+h} \tag{18}$$

and then assess whether one of the two components of GVD is contemporaneously correlated with the three global risk factors in the following regression

$$x_t = \alpha + \beta^h world_t + \gamma^h carry_t + \delta^h dollar_t^{global} + \varepsilon_t \tag{19}$$

Table (15) shows the results of the regressions. The left panel of table (15) presents the results from regression (18). The right panel gives the results from regression (19).

Focusing first on the left panel of table (15), we observe the predictive power of the world stock market returns for Swiss stock market returns. This predictive power is visible at all forecast horizons but is most pronounced at the one-month horizon with the R^2 statistic reaching nearly 4%. This finding confirms Rapach et al. (2013) who show that US stock market returns predict foreign stock market returns. Since the US stock market is the most important component of the world stock market index, our regression results likely echo their findings. The currency risk factors do not have predictive power. None of the regression coefficients of $carry$ or $dollar^{global}$ is statistically different from zero.

However, the right panel of table (15) suggests that global foreign currency risk has an impact on the predictability of Swiss stock market returns through its effect on GVD. GVD is contemporaneously linked to the carry factor. The decomposition of GVD additionally shows that this significant link mainly stems from the exposure of GVD^{new} to $carry$. High returns on the carry factor are associated with contemporaneously low values of GVD (GVD^{new}). Global foreign exchange rate risk, as reflected in *carry*, thus has a direct effect on the predictability of Swiss stock returns as well.

[about here Table (15)]

7 Conclusions

Stylized facts of asset return predictability are mainly based on US evidence. We have used Switzerland as an example of a small, open economy to stress that it cannot be taken for granted that empirical regularities observed in the US pertain to small, open economies as well.

Our main results highlight that differences in the driving forces of variation in asset returns between the US and other economies matter. US asset returns are to a large extent driven by discount-rate news, while the majority of variation in Swiss and other European economies' asset returns reflects cash-flow news. We find that excess returns on Swiss bonds are hardly predictable at all.

Moreover, only one predictor, changes in the weight of large firms in the aggregate Swiss stock market (GVD), exhibits in-sample and out-of-sample predictive power for Swiss stock market returns. The distinction between variation in GVD due to differences in the returns on existing capital between large firms and the aggregate market (GVD^{old}) and differences in net new equity issuances between large firms and the aggregate market (GVD^{new}) is key to understanding its predictive power. It is GVD^{new} that predicts stock market returns in-sample because it captures cash-flow news, which is the main driver of Swiss stock market returns. However, only GVD, the combination of GVD^{new} with GVD^{old}, exhibits out-of-sample predictive power. GVD^{old} forecasts that part of the Swiss stock market returns which is driven by discount-rate news. This additional information seems to be important to forecast the Swiss stock market return out-of-sample.

Finally, we find that the forecast ability for Swiss stock returns varies over time. This time variation is linked to global foreign currency risks thus highlighting the importance of global risks for returns on asset markets of small, open economies.

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Tables

Table 1: What news drives Swiss stock and bond market returns?

stock market return			bond market return		
	CH	US		CH	US
var(NCF)	1.03	0.25	var(NBCF)	1.36	0.13
(95% CI)	(0.76,1.38)	(0.20, 0.32)	(95% CI)	(0.79,2.23)	(0.07,0.24)
var(NRR)	0.01	0.06	var(NBRR)	0.00	0.00
(95% CI)	(0.01,0.01)	(0.04,0.08)	(95% CI)	(0.00,0.00)	(0.00,0.00)
var(NRX)	0.18	0.17	var(NBRX)	0.33	1.20
(95% CI	(0.13,0.23)	(0.13,0.22)	(95% CI)	(0.22,0.51)	(0.63,2.37)
-2cov(NCF,NRR)	-0.03	0.11	-2cov(NBCF,NBRR)	-0.01	0.01
(95% CI)	(-0.06,-0.01)	(0.08,0.15)	(95% CI)	(-0.01,-0.01)	(0.00,0.01)
-2cov(NCF,NRX)	-0.11	0.33	2cov(NBCF,NBRX)	-0.68	-0.31
(95% CI)	(-0.20,-0.02)	(0.26,0.40)	(95% CI)	(-0.89,-0.50)	(-0.42,-0.20)
2cov(NRR,NRX)	-0.08	0.09	2cov(NBRR,NBRX)	0.00	-0.03
(95% CI)	(-0.09,-0.06)	(0.06,0.12)	(95% CI)	(0.00,0.00)	(-0.04,-0.02)

Notes: This table presents the variance decomposition of unexpected excess returns on Swiss and US stock and bond market indexes (obtained from a VAR model) into variances and covariances of the three news components: News about cash-flows (NCF), real interest rates (NRR) and future excess returns (NRX). These statistics are normalized by the variance of the total stock market or bond market return news (NR or NBR) such that they sum to one. In addition, the table gives the 95% confidence interval of the statistics after 1000 bootstrap simulations. The sample period runs from January 1975 to August 2016.
The variables that enter the VAR system are the return on the MSCI Switzerland total return index in excess of the one-month CHF Libor as its first element. The second element is the short-term (here one month) real interest rate. The real rate was obtained using realized, monthly inflation based on a broad consumer price index. Next are the change in the short-term rate, the term spread (ten-year government bond yield minus short-term rate) and the dividend-price ratio. The first four elements are necessary to compute the stock and bond return news. The dividend-price ratio helps alleviate concerns about the choice of news components directly estimated in the VAR.

Table 2: Descriptive statistics of Swiss stock and bond market excess returns

	stock market return	bond market return
mean	1.05	2.57
sample t-stat	0.29	3.47
Sharpe ratio	0.02	0.24
correlation:	-0.28	

Notes: This table provides the mean excess return (in % p.a.) on the Swiss stock and Swiss government bond market over the sample period from January 1999 to August 2016. Below the mean returns, we provide the sample t-statistic of the mean, the Sharpe ratio and the correlation coefficient of stock and bond market returns.

Table 3: Descriptive statistics of potential asset return predictors

Panel A: Descriptive statistics					
	Mean	Std Dev	Max	Min	Auto Correlation
pe	3.06	0.31	3.89	2.48	0.99
dp	-3.87	0.39	-3.20	-4.76	0.97
ts (% p.a.)	1.36	0.69	2.83	0.02	0.93
py	-0.00	0.04	0.03	-0.17	0.98
GVD	-0.02	0.03	0.02	-0.16	0.94
Panel B: Pairwise correlations					
	pe	dp	ts	py	GVD
pe	1	-0.79	-0.08	-0.77	-0.67
dp		1	-0.38	0.68	0.43
ts (% p.a.)			1	-0.20	0.19
py				1	0.56
GVD					1

Notes: This table presents descriptive statistics of the predictor variables under study (Panel A) and their pairwise correlations (Panel B).The adjusted price-earnings ratio, pe, is the log of current Swiss stock prices (index) minus the log of a 10-year moving average of earnings. The log dividend-price ratio, dp, is the log of the sum of monthly dividends over the past year minus the log of this month's MSCI Swiss price index. The term spread, ts, is defined as the spread between the Swiss ten-year government bond yield and the one-month CHF Libor. The net payout yield, py, is defined as the sum of dividends and share buybacks minus the issuance of new equity from $t-\Delta t$ to t and normalized by the aggregate stock market capitalization in t. Finally, we look at GVD, which is defined as the change in the weight of the L largest firms in the aggregate Swiss stock market from $t - \Delta t$ to t. Here, Δt is 12 months for both py and GVD and $L = 50$. The sample period runs from January 1999 to August 2016.

Table 4: In-sample predictability of Swiss stock market excess returns

	h=1		h=3		h=6		h=12	
predictor	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$
$pe(-)$	0.67*	2.19	0.50*	3.38	0.54**	6.78	0.62**	15.69
	(1.49)		(1.91)		(2.23)		(2.55)	
dp	0.56	1.52	0.41	2.19	0.41	3.81	0.35	4.62
	(1.29)		(1.36)		(1.43)		(1.40)	
ts	0.24	0.28	0.28	1.01	0.31	2.26	0.47	8.63
	(0.73)		(0.92)		(0.99)		(1.67)	
py	0.49	1.17	0.17	0.40	0.13	0.40	0.16	1.06
	(0.84)		(0.69)		(0.71)		(0.80)	
GVD	0.32	0.51	0.45*	2.67	0.59**	8.28	0.55**	12.85
	(1.10)		(2.03)		(2.88)		(3.06)	

Notes: This table presents OLS estimates from univariate regressions of h-month ahead Swiss stock market returns on each potential predictor variable described in table (3). The sample period runs from January 1999 to August 2016. We compute heteroskedasticity and autocorrelation robust t-statistics (in parentheses below the estimates) from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h > 0$ because the regressors are defined in such a way that high values predict high excess returns. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 5: In-sample predictability of Swiss bond market excess returns

	h=1		h=3		h=6		h=12	
predictor	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$
$pe(-)$	0.09*	1.06	0.10*	3.42	0.11	6.04	0.10	11.25
	(1.44)		(1.91)		(1.69)		(1.86)	
dp	0.01	0.02	0.02	0.10	0.03	0.36	0.06	3.58
	(0.21)		(0.27)		(0.37)		(0.93)	
ts	0.11**	1.52	0.09*	2.74	0.10*	5.22	0.07	4.87
	(1.73)		(1.59)		(1.74)		(1.64)	
py	0.03	0.13	0.06	1.09	0.08	3.64	0.11	12.12
	(0.50)		(0.84)		(1.27)		(2.41)	
GVD	0.03	0.08	0.03	0.31	0.05	1.08	0.05	2.84
	(0.41)		(0.54)		(0.77)		(0.82)	

Notes: This table presents OLS estimates from univariate regressions of h-month ahead Swiss bond market returns on each potential predictor variable described in table (3). The sample period runs from January 1999 to August 2016. We compute heteroskedasticity and autocorrelation robust t-statistics (in parentheses below the estimates) from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h > 0$ because the regressors are defined in such a way that high values predict high excess returns. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 6: Out-of-sample predictability of Swiss stock and bond market excess returns

stock market returns: R^2_{oos} in %				
predictor	h=1	h=3	h=6	h=12
$pe(-)$	-1.79	-5.36	-6.45	-1.11
dp	-13.07	-27.38	-51.86	-56.69
ts	-0.37	-1.86	-3.31	-12.95
py	-0.50	-2.17	-4.66	-9.73
GVD	-1.75**	0.57	5.75**	5.70**
bond market returns: R^2_{oos} in %				
predictor	h=1	h=3	h=6	h=12
$pe(-)$	0.75	1.43	4.18	10.54
dp	-5.94	-22.19	-41.01	-30.68
ts	0.69	-1.57	-4.43	-19.46
py	-0.15	-0.17	1.69	8.73
GVD	-1.01	-5.20	-14.62	-43.13**

Notes: This table reports the out-of-sample R^2 statistic (R^2_{oos}) proposed by Campbell and Thompson (2008) from out-of-sample forecasts of Swiss stock market returns.
This statistic obeys $R^2_{oos} = 1 - \frac{\sum_{t=tOOS}^{T}(r_t-\hat{r}_t)^2}{\sum_{t=tOOS}^{T}(r_t-\bar{r}_t)^2}$ in which $\hat{r}$ is the predicted value of the stock market excess returns and $\bar{r}_t$ is the historical mean of the return from the beginning of the sample until $T-1$. We test the statistical significance of R^2_{oos} using the Clark and West (2007) test. A positive R^2_{oos} indicates that the mean squared forecast error from the predictions by one of the forecast variables under study is lower than the benchmark, i.e., is lower than predictions using only the historical mean return. We evaluate the out-of-sample predictive ability of the predictors for the forecast period starting in January 2008 ($tOOS$), i.e., the evaluation period for the forecasts runs from January 1999 to December 2007. Then we expand the window monthly from $tOOS$ to T. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 7: Tests of time-varying forecast regression coefficients

stock market returns				
predictor	h=1	h=3	h=6	h=12
$pe(-)$	-2.23	-4.33	-6.24	-6.05
dp	-3.66	-4.79	-5.19	-4.73
ts	-3.96	-5.37	-5.22	-5.72
py	-1.34	-5.6	-8.19*	-5.96
GVD	-9.88**	-8.51**	-9.03**	-7.60*
bond market returns				
predictor	h=1	h=3	h=6	h=12
$pe(-)$	-4.34	-3.58	-3.57	-4.52
dp	-5.62	-5.96	-5.37	-5.38
ts	-7.43*	-7.06	-5.88	-5.31
py	-4.48	-3.05	-2.41	-4.35
GVD	-3.72	-4.08	-4.69	-4.51
Critical Values:	10%	5%	1%	
	-7.14	-8.36	-11.05	

Notes: This table reports the results (and critical values) of a test of time variation in the regression coefficients of the predictive variables (Eliott and Müller, 2006). The critical values apply to the null hypothesis of constant regression coefficients. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 8: Variance decomposition of GVD

	$\frac{var(GVD^{old})}{var(GVD)}$	$\frac{var(GVD^{new})}{var(GVD)}$	$2\frac{cov(GVD^{old},GVD^{new})}{var(GVD)}$
share explained	0.20	0.84	-0.04

Notes: This table presents the variance decomposition of GVD into the parts driven by GVD^{old}, GVD^{new} and the covariance between GVD^{old} and GVD^{new} over our sample period from January 1999 to August 2016.

Table 9: The components of GVD: in-sample predictive power

	stock market return							
	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(%)
GVD^{new}	0.46*	1.03	0.48**	3.10	0.56**	7.61	0.51**	10.92
	(1.46)		(2.25)		(3.18)		(3.14)	
GVD^{old}	-0.25	0.31	-0.02	0.01	0.17	0.69	0.24	2.36
	(-0.90)		(-0.09)		(0.69)		(0.77)	
	bond market return							
	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(%)
GVD^{new}	-0.01	0.03	0.03	0.30	0.06	1.63	0.06	3.25
	(-0.24)		(0.60)		(1.05)		(0.97)	
GVD^{old}	0.11*	1.40	0.02	0.17	-0.00	0.00	0.00	0.02
	(1.67)		(0.42)		(-0.06)		(0.09)	

Notes: This table presents OLS estimates from univariate regressions of h-month ahead Swiss stock and bond market returns on the two components of GVD, which has been described in table (3). GVD^{old} measures the changes in the prices of existing capital of the 50 largest firms relative to the aggregate market from $t-12$ to t. GVD^{new} measures changes in the market capitalisation of the 50 largest firms relative to the aggregate market from $t-12$ to t due to capital raising or capital decreasing activities such as the issuance of new shares or share buy-backs. We compute heteroskedasticity and autocorrelation robust t-statistics (in parentheses below the estimates) from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h > 0$ because the regressors are defined in such a way that high values predict high excess returns. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Table 10: The components of GVD: out-of-sample predictive power

stock market returns: R^2_{oos} in %				
predictor	h=1	h=3	h=6	h=12
GVD^{new}	-0.40	-0.26	1.51	-0.21
GVD^{old}	-2.66	-4.70	-5.16	-3.85
bond market returns: R^2_{oos} in %				
	h=1	h=3	h=6	h=12
GVD^{new}	-0.14	-2.93	-10.64	-36.46*
GVD^{old}	-1.48	-2.45	-2.55	-6.95*

Notes: This table reports the out-of-sample R^2 statistic (R^2_{oos}) proposed by Campbell and Thompson (2008) from out-of-sample forecasts of Swiss stock market returns. The test statistic is explained in the notes to table (6). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Table 11: GVD and its components: predictability of cash-flow and discount rate news

stock return: cash-flow news			bond return: cash-flow news		
GVD	GVD^{new}	GVD^{old}	GVD	GVD^{new}	GVD^{old}
0.16**			0.64		
(2.34)			(0.53)		
	0.18**			0.30	
	(2.75)			(0.28)	
		0.01			1.89
		(0.06)			(0.65)

stock return: discount-rate news			bond return: discount-rate news		
GVD	GVD^{new}	GVD^{old}	GVD	GVD^{new}	GVD^{old}
0.04			0.48		
(1.12)			(1.58)		
	0.01			0.35	
	(0.14)			(1.08)	
		0.19**			0.92
		(2.46)			(1.12)

Notes: This table presents OLS estimates from univariate regressions of one-month ahead cash-flow and discount-rate news driven components of Swiss stock and bond market returns on the two components of GVD. The news components are obtained from a vector autoregressive model described in the notes to table (1). The two components of GVD are described in the notes to table (9). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Table 12: The components of GVD and future GDP growth

	h=1		h=4		h=8		h=12	
predictor	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$
GVD	-0.07	0.09	0.15	0.77	0.36	9.33	0.28	9.39
	(-0.26)		(0.50)		(1.70)		(2.14)	
GVD^{new}	0.15	0.43	0.25	2.19	0.39	10.38	0.30	10.87
	(0.60)		(0.84)		(1.69)		(1.89)	
GVD^{old}	-0.50***	4.74	-0.19	1.33	0.03	0.04	0.01	0.01
	(-2.43)		(-0.79)		(0.12)		(0.04)	

Notes: This table presents OLS estimates from univariate regressions of h-quarter ahead Swiss GDP growth on GVD and its two components. The two components of GVD are described in the notes to table (9). We compute heteroskedasticity and autocorrelation robust t-statistics (in parentheses below the estimates) from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h < 0$ because the regressors are defined in such a way that high values should predict low/negative GDP growth. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Table 13: The components of GVD: time-varying forecast ability?

stock market returns				
predictor	h=1	h=3	h=6	h=12
GVD^{new}	-7.67*	-7.28*	-6.90	-6.17
GVD^{old}	-7.23*	-9.39**	-10.34**	-5.91
bond market returns				
predictor	h=1	h=3	h=6	h=12
GVD^{new}	-3.40	-3.54	-3.70	-4.67
GVD^{old}	-3.99	-4.93	-5.78	-3.90
Critical Values:	10%	5%	1%	
	-7.14	-8.36	-11.05	

Notes: This table reports the results (and critical values) of a test of time variation in the regression coefficients of the predictive variables (Eliott and Müller, 2006). The critical values apply to the null hypothesis of constant regression coefficients. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 14: Stock return forecast regression with conditioning variables

	no interaction		interaction with *world*	
	GVD^{new}	GVD^{old}	w*GVD^{new}	w*GVD^{old}
$r_{t,t+1}$	0.33**	-0.58	-0.06	0.40
	(2.10)	(-1.19)	(-1.03)	(1.34)
$r_{t,t+3}$	0.27**	0.28	-0.03	-0.06
	(2.36)	(0.52)	(-1.00)	(-0.64)
$r_{t,t+6}$	0.25**	0.41*	-0.03	-0.05
	(2.99)	(2.10)	(-1.33)	(-0.64)
$r_{t,t+12}$	0.23**	0.31	-0.03	0.05
	(2.90)	(1.29)	(-1.19)	(1.19)

	interaction with *carry*		interaction with $dollar^{global}$	
	c*GVD^{new}	c*GVD^{old}	d*GVD^{new}	d*GVD^{old}
$r_{t,t+1}$	-0.10	0.57***	-0.01	-0.37*
	(-1.20)	(2.53)	(-0.06)	(-1.52)
$r_{t,t+3}$	-0.03	0.25*	0.01	-0.40***
	(-0.74)	(1.66)	(0.24)	(-2.66)
$r_{t,t+6}$	-0.01	0.06	0.00	-0.19**
	(-0.44)	(0.66)	(0.10)	(-2.12)
$r_{t,t+12}$	-0.05**	-0.01	0.04	-0.11
	(-2.15)	(-0.10)	(1.42)	(-1.38)

Notes: This table presents OLS estimates from regressions of h-month ahead stock market returns on the two GVD components (GVD^{new} and GVD^{old}) under the assumption that the regression coefficients (and, hence, the forecast ability) varies over time. This time variation is modelled as a linear function of three global risk factors: the world stock market return denominated in local currencies (*world*), the (foreign currency) carry factor (*carry*) and the global dollar factor ($dollar^{global}$). The global risk factors are standardized in a way that allows a comparison of the regression coefficients of interaction terms with the GVD components and the uninteracted terms. For example, w is defined as $w = 1 + \frac{world_t}{\sigma(world)}$, with σ representing the standard deviation and *world* the "raw" world stock market return. The two components of GVD are described in the notes to table (9). The carry factor is the return difference between foreign currency portfolios consisting of high interest rate and low interest rate currencies. The global dollar factor is defined as the return difference between foreign currency portfolios consisting of currencies with high exposures to average US dollar exchange rate changes and currencies with low exposures to average US dollar exchange rate changes. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Table 15: The direct effects of global risk on Swiss stock return predictability

	expected returns			
	world	*carry*	$dollar^{global}$	$R^2(\%)$
$r_{t,t+1}$	0.24***	-0.01	0.02	3.67
	(2.83)	(-0.06)	(0.21)	
$r_{t,t+3}$	0.12**	-0.03	-0.03	1.57
	(2.61)	(-0.34)	(-0.43)	
$r_{t,t+6}$	0.09**	-0.06	-0.02	2.11
	(2.41)	(-1.01)	(-0.50)	
$r_{t,t+12}$	0.06*	-0.04	-0.02	0.73
	(2.10)	(-0.69)	(-0.99)	
GVD and components: contemporaneous regression				
GVD	0.11	-0.26**	-0.04	2.55
	(1.35)	(-2.15)	(-0.61)	
GVD^{new}	0.14*	-0.22*	-0.04	2.99
	(1.69)	(-1.83)	(-0.66)	
GVD^{old}	-0.03	-0.03	-0.00	0.30
	(-0.84)	(-0.98)	(-0.13)	

Notes: The upper panel of this table reports OLS estimates from regressions of h-month ahead stock market returns on three global risk factors: the return on a world stock market index (*world*), the (foreign currency) carry factor (*carry*) and the global dollar factor ($dollar^{global}$). These factors are described in the notes to table (14). The lower panel gives OLS estimates from regressions of GVD and its two components (explained in the notes to table (9)), on the contemporaneously measured three global risk factors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period runs from January 1999 to August 2016.

Appendix

Swiss stock market and GVD

Swiss stock market: Institutional details & data

The sample period for assessing asset return predictability in Switzerland is constrained by the availability of data. To construct the payout yield (py) or GVD, we have to use Swiss stock market data that are only available from May 1996 onwards, when electronic asset trading was introduced in Switzerland. We have information about the total market capitalization of all shares of all Swiss non-financial and financial firms traded electronically on the Swiss exchange. When compiling the market capitalizations of listed Swiss firms we take into account that different types of shares of one company could be traded at the same time. This is a typical feature of the Swiss and German stock markets.[6] The total market capitalization of a firm is the sum of the value of the different share types.

In addition, this database provides us with a decomposition of changes in total market capitalization due to changes in the price of existing capital and net new equity capital. Thus, we are able to directly calculate the two components of GVD and, using aggregates, the payout yield. Our sample period starts in January 1999 because of the 12-month horizon to construct GVD, which requires two full years of observations of net new capital activities. Table (16) summarizes what information about each share type's market capitalization is available to us.

[6] There are two broad categories of shares that grant voting rights to shareholders. Among these shares, one can distinguish shares that inform the firm about the name of the shareholder (in German: "Namensaktien") and shares that inform the firm only about the depository institutions at which the shares are held (in German: "Inhaberaktien"). In addition, we take into account "Partizipationsscheine", which are shares that do not grant any voting rights to shareholders. Many firms in our sample use at least two of the three different types of shares at the same time.

Table 16: Details of share market capitalization at monthly frequency

Total market value at the end of previous month
+ Increase in market value (new listings, share capital increases)
- Reduction in market value (delistings, share capital decreases, par value redemptions, dividend payments)
+ Price changes (+/-)
= **Total market value at the end of month**

From January 1999 to August 2016, the total number of firms listed on the Swiss stock exchange varies from 234 to 319. Figure (1) depicts the number of firms that make up the total market, M, over time. There has been a clear downward trend in the number of listed firms since the end of the technology firm boom around 2001/2002.

Figure 1: Total number of firms listed on the Swiss stock exchange

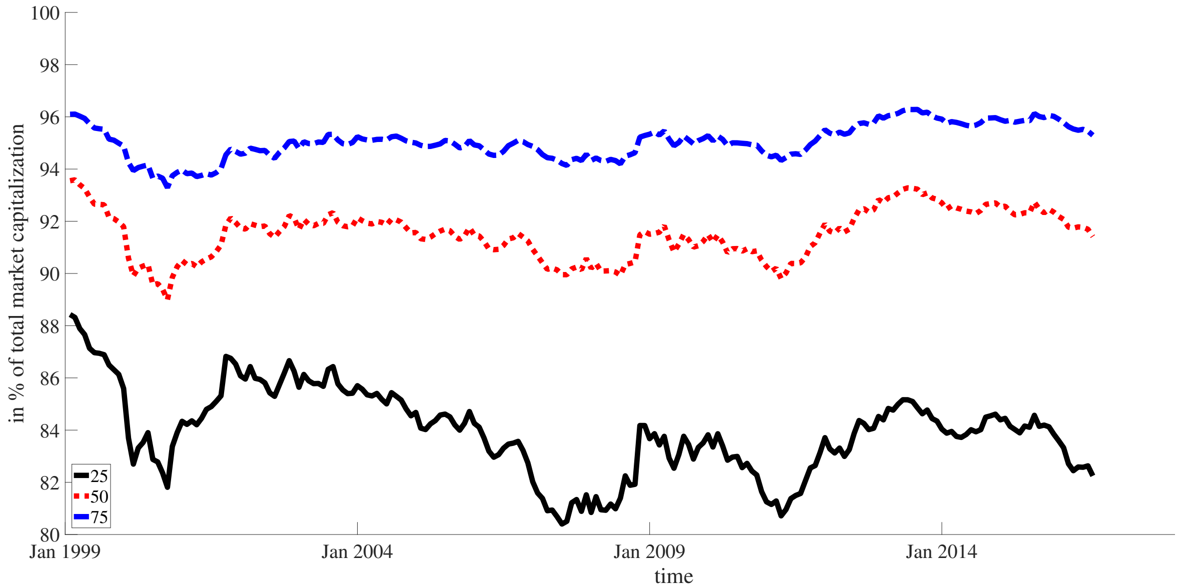
However, despite the recent fall in the number of firms, the total market capitalization of the Swiss stock market has increased in recent years. Figure (2) presents the time series of the total market capitalization.

Figure 2: Total Swiss stock market capitalization over time

This finding suggests that small firms grew larger over the sample period. This is reflected in the descriptive statistics of GVD presented in table 3 in the main body of the paper. The mean value of GVD is negative, which suggests that the total market capitalization of the total market (mainly composed of small firms) grew more than the market capitalization of the largest firms. The small firms on the Swiss stock market have become larger over our sample period.

Our baseline results presented in the main text rely on the formation of GVD using the 50 largest firms on the Swiss stock market. We opted for 50 firms to ensure that the number of largest firms relative to the total number of firms is relatively small. However, on average, the 50 largest firms comprise close to 90% of the total stock market capitalization. We also evaluated GVD versions using the 25 and the 75 largest firms in the sample for comparison. Even the 25 largest firms comprise more than 80% of the total stock market capitalization. Figure (3) illustrates this point.

Figure 3: Share of total market capitalization by L largest firms



Empirical results for alternative definitions of GVD

Our baseline version of GVD focuses on the 50 largest firms of the Swiss stock market relative to the aggregate market, GVD^{50}. These 50 largest firms comprise approximately 90% of the total market capitalization during our sample period. In robustness checks we assess the performance of GVD constructed from the 25 and 75 largest firms on the Swiss stock market as well. The pairwise correlations between the three GVD series are high, varying between 0.93 and 0.99.

Not surprisingly, the regression results for GVD^{25} and GVD^{75} are similar to the baseline evidence obtained with GVD^{50}. Table (17) presents the in-sample forecast regression results for the two alternative definitions of GVD. These results suggest that the forecast ability of GVD^{25} for stock returns is less pronounced than that of GVD^{75}. As in the baseline results, bond market returns are not predictable.

Table 17: In-sample predictability of stock and bond market excess returns

	stock market return							
	h=1		h=3		h=6		h=12	
predictor	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$
GVD^{25}	0.11	0.06	0.29	1.13	0.43*	4.44	0.50**	10.61
	(0.41)		(1.27)		(2.09)		(2.66)	
GVD^{75}	0.28	0.39	0.40*	2.17	0.53**	6.82	0.57**	13.53
	(0.95)		(1.66)		(2.69)		(3.29)	
	bond market return							
	h=1		h=3		h=6		h=12	
predictor	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$	$\hat{\beta}$	$R^2(\%)$
GVD^{25}	0.05	0.35	0.03	0.28	0.03	0.56	0.03	1.20
	(0.82)		(0.50)		(0.66)		(0.65)	
GVD^{75}	0.01	0.02	0.02	0.10	0.04	0.83	0.05	2.60
	(0.22)		(0.32)		(0.78)		(0.88)	

Notes: This table presents OLS estimates from univariate regressions of h-month ahead Swiss stock and bond market returns on GVD constructed with data of the 25 (GVD^{25}) or 75 (GVD^{75}) largest firms in the Swiss stock market. The sample period runs from January 1999 to August 2016. We compute heteroskedasticity and autocorrelation robust t-statistics (in parentheses below the estimates) from a wild bootstrap procedure that tests the null hypothesis of $\hat{\beta}^h = 0$ against the alternative that $\hat{\beta}^h > 0$ because the regressors are defined in such a way that high values predict high excess returns. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Out-of-sample regression results confirm the impression that the lower the number of firms used to calculate GVD, the lower its predictive power for Swiss stock market returns. In contrast to the baseline results and the evidence for GVD^{75}, GVD^{25} does not exhibit out-of-sample predictive power for Swiss stock returns. Table (18) presents the detailed results.

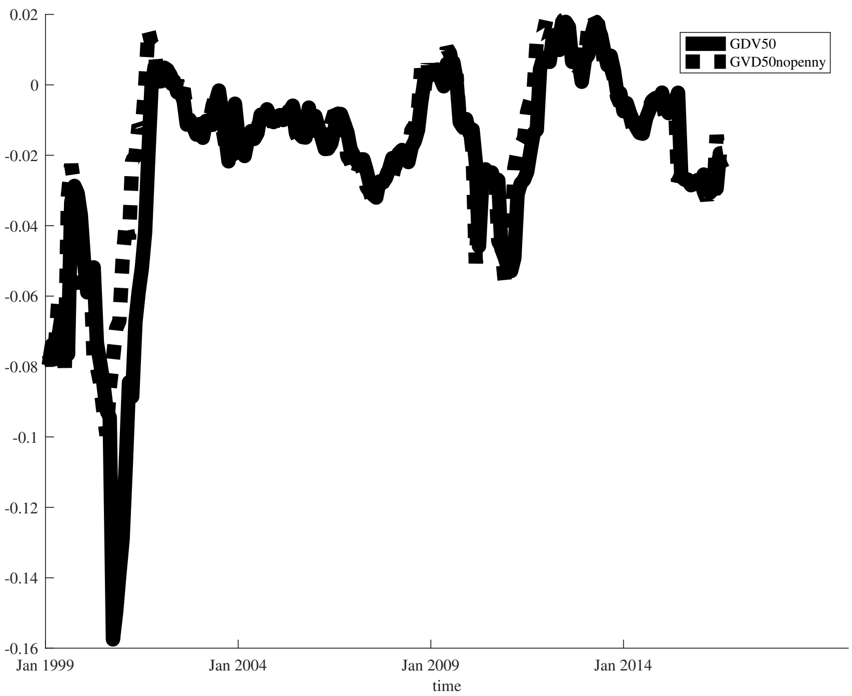
Table 18: Out-of-sample predictive power for stock and bond market returns

stock market returns: R^2_{oos} in %				
predictor	h=1	h=3	h=6	h=12
GVD^{25}	-1.76	-0.90	1.39	6.19
GVD^{75}	-1.32**	-0.02	3.15**	5.13**
bond market returns: R^2_{oos} in %				
predictor	h=1	h=3	h=6	h=12
GVD^{25}	-0.23	-1.85	-4.06	-17.49*
GVD^{75}	-0.38**	-2.00*	-6.11	-29.20*

Notes: This table reports the out-of-sample R^2 statistic (R^2_{oos}) proposed by Campbell and Thompson (2008) from out-of-sample forecasts of Swiss stock market returns.
This statistic obeys $R^2_{oos} = 1 - \frac{\sum_{t=tOOS}^{T}(r_t-\hat{r}_t)^2}{\sum_{t=tOOS}^{T}(r_t-\bar{r}_t)^2}$ in which $\hat{r}$ is the predicted value of the stock market excess returns and $\bar{r}_t$ is the historical mean of the return from the beginning of the sample until $T-1$. We test the statistical significance of R^2_{oos} using the Clark and West (2007) test. A positive R^2_{oos} indicates that the mean squared forecast error from the predictions by one of the forecast variables under study is lower than the benchmark, i.e. lower than predictions using only the historical mean return. We evaluate the out-of-sample predictive ability of the predictors for the forecast period starting in January 2008 ($tOOS$), i.e. the evaluation period for the forecasts runs from January 1999 to December 2007. Then we expand the window monthly from $tOOS$ to T. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Our results also survive when we adjust for so called penny stocks, i.e., stocks whose prices are extremely low. We excluded all stocks in the construction of GVD whose prices vary between zero and one franc. All of the regression results remain qualitatively the same. Figure (4) illustrates why. The correlation between our baseline version of GVD (constructed with the 50 largest firms on the Swiss stock market) and the corresponding version that corrects for penny stocks is relatively high. The two series deviate from each other around the time of the burst of the technology firm boom at the beginnign of the 2000s. However, they closely co-move since then.

Figure 4: GVD vs. GVD adjusted for penny stocks



Foreign currency risk factors: construction and data

We employ two global foreign currency risk factors in our assessments of the impact of global risks on asset predictability in Switzerland. The first global foreign currency risk factor is the carry factor. The carry factor is constructed from returns on portfolios of US dollar exchange rates from t to $t+1$. The allocation of US dollar exchange rate returns into portfolios at time t is based on the respective foreign currency's interest rate differential (forward premium) vis-à-vis the US in t. These interest-rate differential sorted portfolios are rebalanced every month. The carry factor is the return difference between the portfolio consisting of the foreign currencies with the highest interest rate differential to the US and the portfolio consisting of the foreign currencies with the lowest interest rate differential to the US. Lustig et al. (2011) show that the carry factor, defined in this way, reflects the differences in exposure to a global shock between high and low interest rate currencies. The returns on the carry factor are thus independent of currency-specific risks. Hence, the carry factor is a global risk factor.

Our second global foreign currency risk factor is the global dollar factor recently introduced by Verdelhan (2015). Construction of the global dollar factor is based on portfolios of US dollar exchange rate returns that are sorted into bins according to their (time-varying) exposure (beta) to average US dollar exchange rate returns. Conditional on a positive average interest rate differential between the US and all of the developed markets in the sample, the investor takes a long position in the dollar-beta portfolios. She takes a short position if the average interest rate is negative. These dollar-beta portfolios are rebalanced every month. The return differences between dollar-beta sorted foreign currency portfolios are significant. Returns increase from low dollar-beta to high dollar-beta portfolios. Verdelhan (2015) shows that this "dollar risk" reflects compensation for exposure to a US-dollar-specific and a global shock, which is different from the global shock driving returns on the carry factor. Taking the difference between returns on the highest and lowest dollar-beta portfolios eliminates the US-specific risks and can thus be interpreted as the global component of the dollar factor.

To construct the two global risk factors, we closely follow Verdelhan (2015) and use monthly US-dollar spot and one-month forward exchange rates from 39 different countries (currency areas). The source of this data is Thompson/Reuters. The countries (currency areas) are the following: Australia, Austria, Belgium, Canada, China (Hong Kong), Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South

Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom and the euro area (since January 1999). All euro area countries are excluded from the sample after the introduction of the euro.

We first sort these foreign currencies into quintiles (five portfolios) based on their past month's forward premium/interest rate differential. Then we compute the carry factor as the difference between the excess return on the foreign currency portfolio formed from the highest interest rate differential currencies (highest quintile) and the excess return on the foreign currency portfolio formed from the lowest interest rate differential currencies (lowest quintile). Because we assume that covered interest rate parity (CIP) holds, i.e., the forward premium is approximately equal to the interest rate differential, we follow Verdelhan (2015) and exclude the following observations due to large deviations from CIP: South Africa from July to August 1985, Malaysia from August 1998 to June 2005, Indonesia from December 2000 to May 2007, Turkey from October 2000 to November 2001 and the United Arab Emirates from June to November 2006.

Following Verdelhan (2015), we obtain the global dollar factor from foreign currency portfolios based on their exposures to the dollar factor (average US dollar exchange rate return). The exposures are calculated from rolling window regressions over a 60-month window. The dollar exposure of a particular currency at time t is the estimated coefficient of that currency with the dollar factor from a rolling window regression from $t-60$ to $t-1$. The explanatory variables in this regression are a constant, the dollar factor, the carry factor, the bilateral forward premium in excess of the average forward premium across all currencies and the carry factor interacted with the forward premium term mentioned before. Again, we sort foreign currencies into quintiles (five portfolios) at time t based on their past dollar exposure. These portfolios are rebalanced every month. The global dollar factor is the difference between returns on the highest and lowest dollar-beta foreign currency portfolios (quintiles).

Table (19) provides some descriptive statistics of the returns on the two global foreign currency risk factors over our sample period from January 1999 to August 2016. We observe that the carry factor offered a return of approximately 9% p.a. over this time period. The global dollar factor delivered a return that is half that of the carry factor. The correlation between the two risk factors is positive but relatively low. The correlation coefficient is 0.35.

Table 19: Descriptive statistics of global foreign currency risk factors

	$carry$	$dollar^{global}$
mean	8.99	4.52
sample t-stat	4.56	1.73
Sharpe ratio	0.31	0.12
correlation:	0.35	

Notes: This table provides the mean excess return (in % p.a.) on the carry and the global dollar factor over the sample period from January 1999 to August 2016. Below the mean returns, we provide the sample t-statistic of the mean and the Sharpe ratio as well as the correlation coefficient between the two risk factors.

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