Journal of *Risk and Financial Management*

MDPI

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Spillovers and Asset Allocation

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Abstract: There is a large and growing literature on spillovers but no study that systematically evaluates the importance of spillovers for portfolio management. This paper provides such an analysis and demonstrates that spillovers are fully embedded in estimates of expected returns, variances, and correlations and that estimation of spillovers is not necessary for asset allocation. Simulations of typical empirical spillover settings further show that same-frequency spillovers are often negligible and spurious.

Keywords: spillover; return spillovers; volatility spillovers; portfolio optimization; asset allocation

JEL Classification: C32; C58; G11

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Citation: Hoang, Lai T., and Dirk G. Baur. 2021. Spillovers and Asset Allocation. *Journal of Risk and Financial Management* 14: 345. https://doi.org/10.3390/jrfm14080345

Academic Editor: Robert Brooks

Received: 17 June 2021
Accepted: 21 July 2021
Published: 27 July 2021

1. Introduction

Spillovers provide information about the connectedness of markets and market efficiency. More specifically, spillovers can identify the source of any connectedness or correlation and estimate the share of information not fully priced into stock or asset prices on, say, a daily basis. However, we demonstrate that identification or estimation of spillovers is not necessary for asset allocation. Assume we estimate a model to identify volatility spillovers and find that a significant part of the volatility of market B is the result of a spillover from market A. While this finding explains the role of market A for market B, we will show in this study that it is not relevant for asset allocation because the volatility spillover is fully embedded in the variance of asset B. The same is true for return spillovers on expected returns and on correlations.

The interdependence and connectedness of markets is a widely studied topic (e.g., Forbes and Rigobon 2002; French and Poterba 1991; Goetzmann et al. 2001; Pukthuanthong and Roll 2015; Solnik and Watewai 2016) and so are spillovers from one market to another, across assets or asset classes (e.g., Engle et al. 1990; Eun and Shim 1989; King and Wadhwani 1990, for earliest studies of spillovers).

A large body of the literature analyzes how shocks spill over from one market (or asset) to another. Early studies (e.g., Arshanapalli and Doukas 1993; Cheung and Ng 1996; Eun and Shim 1989; Hamao et al. 1990; Lin et al. 1994) mainly focus on the interconnectedness between the US stock market and other international stock markets, whereas subsequent studies extend the scope to regional stock markets such as Scandinavian (Booth et al. 1997) or European markets (Bartram et al. 2007), and to spillovers between spot and futures markets (Tse 1999). Significant efforts have also been devoted to examine other asset classes, including energy markets (Ji et al. 2019; Rittler 2012; Xu et al. 2019), credit markets (Collet and Ielpo 2018), commodity markets (Dahl and Jonsson 2018; Green et al. 2018), bond markets (Reboredo 2018), or currency exchanges (Francq et al. 2016; Greenwood-Nimmo et al. 2016). Other studies examine asymmetric volatility spillovers, e.g., whether bad volatility spillovers dominate good volatility spillovers (Barndorff-Nielsen et al. 2008; Baruník et al. 2016; BenSaïda 2019; Xu et al. 2019).

Diebold and Yilmaz (2009) distinguish return and volatility spillovers between markets and propose a spillover index to analyze such phenomena. The authors apply this index to global equity markets. In a subsequent paper, Diebold and Yilmaz (2012) focus on volatility spillovers across US stock, bond, foreign exchange, and commodity markets. More recent empirical studies on return and volatility spillovers include Baruník et al. (2016); Dahl and Jonsson (2018); De Santis and Zimic (2018); Kang et al. (2017); Symitsi and Chalvatzis (2018); Yang and Zhou (2017); Yarovaya et al. (2017), among many others.

However, the large and growing literature on spillovers[1] is in stark contrast to the absence of studies that analyze the importance of spillovers for asset allocation.[2] In fact, many studies argue that the estimation of spillovers is important for portfolio optimization and diversification but do not explicitly test this argument, and no study provides both theoretical and empirical evidence for such arguments. This paper fills this gap in the literature and contributes with a theoretical and empirical analysis of the importance of spillovers. More specifically, we investigate how the identification and estimation of spillovers affect the way investors allocate assets to an optimal portfolio and its performance.[3]

The study of the spread of shocks from one market or asset at time t to another market at time $t + 1$ can lead to a more fundamental understanding of interdependencies and it is intuitive that identification of the origin and the effect of spillovers are important. However, it is equally important to realize that return spillovers are fully embedded in returns and thus in contemporaneous correlations of returns and that variance spillovers are fully embedded in variances. For example, the daily (contemporaneous) return correlation of two assets may be driven by intra-day return spillovers between the two assets: if there is price-relevant news for firm A at 2 pm that spills over to firm B with a 2-h lag at 4 pm, the contemporaneous return correlation at 2 pm would be zero but the contemporaneous correlation at 4 pm including the news at 2 pm and 4 pm would be different from zero. The resulting contemporaneous return correlation at the daily frequency is due to non-contemporaneous spillovers occurring intra-day, i.e., at a higher frequency. Similar relationships hold for weekly correlations and daily spillovers, monthly correlations and weekly spillovers, and so forth. This relationship also holds for variances. A variance shock of source A at 2 pm that affects the variance of asset B (variance spillover) at 4 pm is embedded in the variance of asset B at 4 pm. If the returns and variances are viewed as the sum of all spillovers from different sources, assets or simply information (e.g., announcements), they fully explain the average returns and variances of every asset.

More formally, we can write the above spillover—return, variance, and correlation—relationship as follows:

$$PI(f) = \sum_{i=1}^{I} s_i(f + j) + c \tag{1}$$

where PI denotes one of the three asset characteristics—returns, variances, or correlations—at frequency f and s_i denotes the i-th (out of I spillovers) spillover at frequency $f + j$ where j can be zero (same frequency) or larger than zero (higher frequency). The parameter c captures the part of PI that is not explained by the spillover s_i. The larger c is, the smaller is the role of the spillovers and vice versa. For example, in a perfectly efficient market, daily return spillovers should be insignificant and not contribute to $PI(f = daily)$ implying that c is large.[4]

The importance of the frequency in assessing spillovers and correlations has, to the best of our knowledge, not been studied before either. A loosely related study is Gilbert et al. (2014) who analyze the role of the return frequency in estimating stock market betas and find that betas estimated from high-frequency returns are less precise than betas estimated from lower-frequency returns. They explain the difference with uncertainty about the effect of systematic news and information opacity. This study offers an alternative interpretation based on spillovers: high-frequency returns contain less spillovers and thus less information than low-frequency returns.

We demonstrate that return and volatility spillovers have significant effects on asset allocation but are fully embedded in estimates of expected returns, variances, and correlation which are ingredients to construct mean-variance optimal portfolios according to the Modern Portfolio Theory (Markowitz 1952).[5] Therefore, identification of these spillovers is not necessary for portfolio optimization and does not change the optimal weights. In addition, we demonstrate that the marginal increase in explanatory power of return and volatility spillovers is generally less than 1% and potentially negligible. The findings thus highlight that the estimation of spillovers is not as important for asset allocation as implied by the large and growing literature on spillovers. Thus, practitioners do not need to estimate spillovers but can focus on classical ingredients of portfolio optimization to form their portfolios.

The rest of the paper is structured as follows. Section 1 contains the simulation study that analyses return and volatility spillovers. Section 2 analyzes return and volatility spillovers empirically using 30 stocks of the Dow Jones Industrial Average and Section 3 summarizes the main results and concludes.

2. Simulation Study

Our simulation is designed to answer the main research questions: How are spillovers linked to correlations, returns and variances, and how important are spillovers for asset allocation compared with those characteristics. We use 2-asset examples and 2-asset portfolios for presentation purposes and show that our results also hold for large N-asset portfolios.

2.1. Return Spillovers

For the return spillovers case, let $P_{0,d}$ denote the "non-spillover" portfolio that is formed by two assets X and Y in which we only allow a contemporaneous correlation but not a spillover between returns of X ($x_{d,t}$) and Y ($y_{d,t}$):

$$\begin{aligned} x_{d,t} &= af_t + \varepsilon_{1,t} \\ y_{d,t} &= I_a af_t + \varepsilon_{2,t} \end{aligned} \tag{2}$$

where a and I_a are prespecified parameters determining the contemporaneous correlation between X and Y, I_a is an indicator that equals 1 if $a > 0$, and -1 otherwise. Negative I_a identifies a negative contemporaneous correlation between $x_{d,t}$ and $y_{d,t}$, and vice versa. f_t, $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ are randomly generated such that $f_t \sim \mathcal{N}(0, sd)$, $\varepsilon_1, \varepsilon_2 \sim \mathcal{N}(er, sd)$, $er \in [0.03, 0.08]$, and $sd \in [1, 2]$.[6] Then we construct the "spillover" portfolio $P_{S,d}$ that is similar to P_0 in all aspects except that there is an unidirectional return spillover between two assets. Let X denotes the spillover-giving asset and Z denotes the spillover-receiving asset in the portfolio $P_{S,d}$, then

$$\begin{aligned} x_{d,t} &= af_t + \varepsilon_{1,t} \\ z_{d,t} &= I_a af_t + bx_{d,t-1} + \varepsilon_{3,t} \end{aligned} \tag{3}$$

where b is the prespecified parameter determining return spillover from X to Z, $\varepsilon_3 \sim \mathcal{N}(er, sd)$. a, I_a, er, and sd are defined similarly to Equation (2). We employ various levels of a and b to cover a broad range of possible scenarios, i.e., $a \in \{-0.5, 0, 0.5\}$ and $b \in [-0.3, 0.3]$ incrementing by 0.03. We set the mean value of f to zero to eliminate possible effects of contemporaneous correlation on expected returns and to allow identification of the role of spillovers on either characteristics.

For illustration purposes, we assume that the generated series $x_{d,t}$, $y_{d,t}$, and $z_{d,t}$ of the corresponding assets X, Y, and Z are daily returns (denoted by the subscript d) but the results apply to any frequency such as intraday, hourly, or 1-min returns. Likewise, when we aggregate "daily" returns into "weekly" returns, the aggregated return series can also be interpreted at any lower frequency.

For each value of a and b, we run 1000 iterations. For each iteration, we simulate X, Y, and Z using the same set of $a, b, f, \varepsilon_1, \varepsilon_2, \varepsilon_3$. Under this setting, $P_{0,d}$ is considered the base case, and any observed difference between $P_{0,d}$ and $P_{S,d}$ and equally between Y and Z are purely associated with the return spillover from X to Z. We generate 2100 observations for each series, then discard the first 100. We assume that investors optimize their portfolios with either the minimum variance or the maximum Sharpe ratio target. To estimate those targets, we set the daily risk-free rate of 0.07%, which is computed as the average of daily risk-free rate from Kenneth French's data library during 1998–2018.[7] Then, for the case of the minimum variance target, we calculate the difference between the standard deviation of $P_{S,d}$ and $P_{0,d}$, and the differences in weights assigned to assets X and Z versus X and Y. Similarly, if $P_{S,d}$ and $P_{0,d}$ are constructed targeting the maximum Sharpe ratio, we compute the difference in Sharpe ratios of $P_{S,d}$ and $P_{0,d}$, along with the difference in constituents' weights. With 1000 iterations corresponding with each combination of a and b, we end up with 1000 observations to run a statistical t-test on those differences. Statistically significant differences would imply that the presence of spillovers affects the optimal portfolios as well as how investors allocate assets to maintain such optimum.

To examine how high frequency spillovers affect asset allocation if lower frequency data is used, we aggregate each five (daily) consecutive observations in each series $x_{d,t}$, $y_{d,t}$, and $z_{d,t}$ to generate weekly return series. Again, the "daily" and "weekly" used here are only for illustration purposes; they can be interpreted as high-frequency and low-frequency at any level. For each iteration, the portfolios $P_{S,wk}$ and $P_{0,wk}$ are formed based on weekly returns, then their characteristics are compared in a similar manner as for the daily return series.

2.1.1. Influence of Return Spillovers on Asset Characteristics

As the Modern Portfolio Theory (Markowitz 1952) is based on expected returns, with variances and correlations of assets as key input variables, we start our analysis by examining whether return spillovers affect those characteristics at the same frequency. Specifically, given the simulated daily returns series, we compare expected returns and standard deviations of asset Y with those of asset Z. As there is a return spillover from X to Z but not to Y, any difference between Y and Z can be interpreted as caused by the return spillover. Figure 1 shows that the presence of return spillovers has effects on the characteristics of the asset that receives it. Specifically, the higher the positive (negative) daily return spillover, the higher (lower) the expected daily returns (Figure 1a). Meanwhile, Figure 1b shows that a higher return spillover (both positive and negative) result in a higher variance of the spillover-receiving asset. Figure 1c shows that if the "initial" level of correlation is different from zero, an increase of return spillovers results in a decrease of correlation (hereafter for correlation and return/volatility spillovers, by increase we mean that the correlation/spillover is becoming either more positive or more negative, and vice versa). More specifically, given an "initial" positive (negative) correlation, if return spillover increases, the resulting correlation will be less positive (negative). Those results are intuitive, as a positive (negative) return spillover adds positive (negative) disturbance to the spillover-receiving asset's "own" return and thus makes its observed expected return higher (lower) (Figure 1a). Such disturbance also leads to higher volatility of the asset's return (Figure 1b). Consequently, as one asset becomes more volatile while the other does not change, their correlation should decrease (less positive/negative). Meanwhile, if there is no "initial" correlation between two assets, such change of the volatility of one asset does not affect its correlation with the other (Figure 1c). Note that the effect of return spillovers on correlations is economically marginal as the magnitudes of the differences are very small (the maximum absolute value is less than 0.01 at the very high level of return spillover, i.e., 0.3).

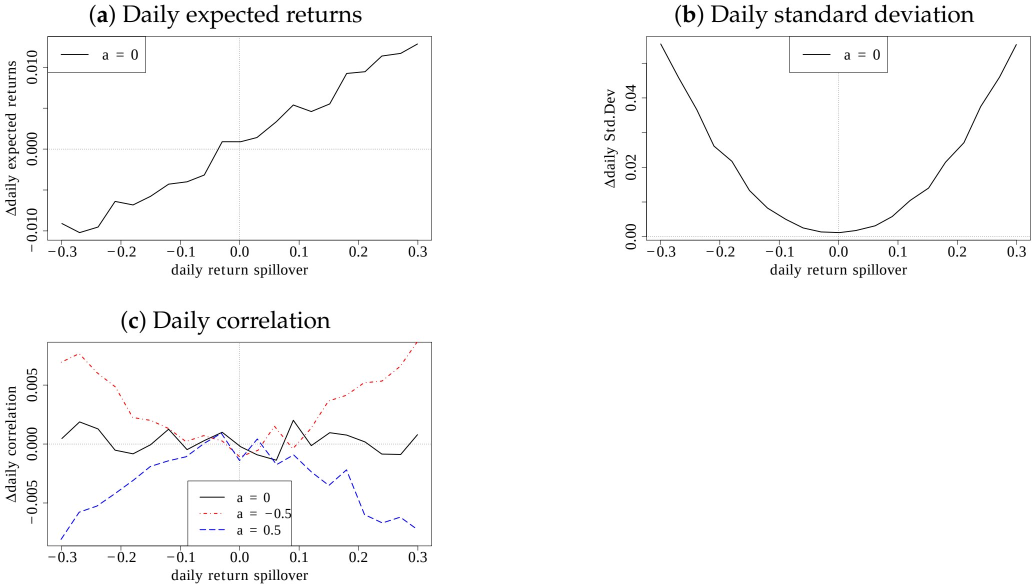


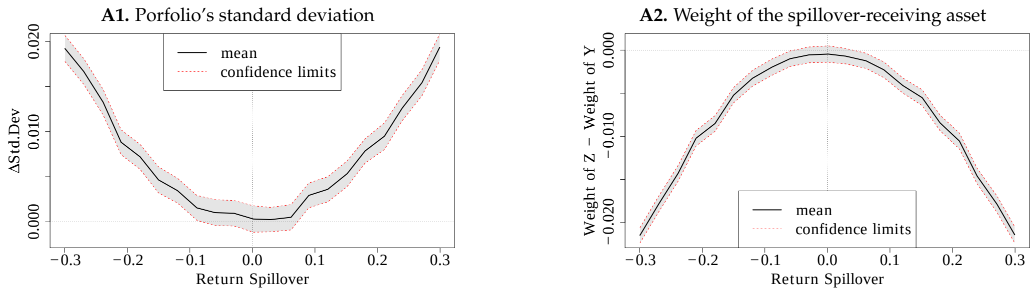
Figure 1. Effects of return spillovers on the same frequency assets' characteristics. This figure presents the effects of daily return spillovers on expected returns (**a**), standard deviation of the spillover-receiving asset (**b**), and the return correlation between spillover-giving and spillover-receiving assets (**c**) at daily level. We use "daily" for the illustration purpose; the results apply to any other frequency. Because of overlaps between lines, we only present the case with a = 0 in (**a**,**b**). The graphs for $a = -0.5$ and a = 0.5 are qualitatively similar.

2.1.2. Influence of Return Spillovers on Portfolio Characteristics

We now turn to the univariate effects of daily return spillovers on optimal portfolios constructed by daily returns. The results are presented in Figure 2. Panel A demonstrates that if there is an increase in daily return spillovers, i.e., more positive/negative, the standard deviation of the minimum variance portfolio will increase, and to minimize portfolio's variance, investors should allocate less wealth to the asset that receives the return spillover (Panel B). We suggest that the explanations for such observed relationships can be derived from the links between return spillovers and assets' characteristics in Figure 1. Specifically, if the return spillover becomes more positive (negative), the volatility of the spillover-receiving asset would increase, resulting in higher overall variance of the portfolio. In the meantime, as the volatility of the spillover-receiving asset increases, its proportion should be reduced to maintain the portfolio's minimum variance. Note that there may be an opposing effect from correlation, i.e., the return spillover reduces the positive correlation (Figure 1c) and thus decreases the portfolio's minimum variance. However, as explained above, the correlation effects are channeled through the volatility effects and thus are dominated by the latter.

Links in Figure 1 also provide intuitive explanations for the positive trends observed in Panel B of Figure 2, which shows significant univariate relations between return spillovers and the maximum Sharpe ratio portfolio. Specifically, a more negative return spillover results in a lower expected return (a component of the Sharpe ratio's numerator) and a higher variance of the spillover-receiving asset (a component of the Sharpe ratio's denominator), which in turn lead to lower maximum Sharpe ratio. Further, as a result of the decrease in expected returns and increase in the return variance, investors should allocate less on the spillover-receiving asset to maintain the portfolio performance. The link becomes less straightforward when the return spillover is positive as both the expected return and the variance of the spillover-receiving asset move in the same direction if the return spillover changes. However, it is likely that the effects of the expected returns dominate that of the volatility, resulting in higher maximum Sharpe ratio and higher weight of the spillover-receiving asset.

Panel A: Minimum variance portfolio constructed by daily returns



Panel B: Maximum Sharpe ratio portfolio constructed by daily returns

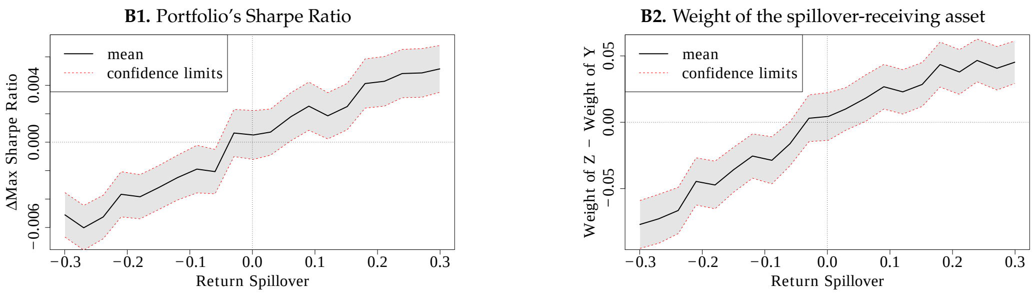


Figure 2. Return spillovers and portfolio optimization using the same frequency returns. This figure presents the differences in characteristics of optimal portfolios formed by daily returns with and without daily return spillover. We use "daily" for the illustration purpose; the results apply to any other frequency. Panel A presents the differences in standard deviation and in the weight of the spillover-receiving asset in the minimum variance portfolio. Panel B presents the differences in the Sharpe ratio and in the weight of the spillover-receiving asset in the portfolio targeting maximum Sharpe ratio. Shaded areas represent 1% confidence intervals. For brevity, we only report graphs with $a = 0$. The graphs with $a = -0.5$ and $a = 0.5$ are qualitatively similar.

2.1.3. Return Frequencies and Asset Characteristics

We further examine the influence of daily return spillovers on portfolios formed by lower frequency returns, i.e., weekly returns. We form weekly returns series x_{wk}, y_{wk}, and z_{wk} by aggregating blocks of five consecutive observations in each series x_d, y_d, and z_d. The relationships between daily return spillovers and differences in characteristics of z_{wk} and y_{wk} are presented in Figure 3. The positive link between daily return spillovers and weekly expected returns remains as in the case of daily expected returns (Figure 3a). However, that of weekly standard deviation and weekly correlations is different from the daily level. Specifically, daily return spillovers positively affect weekly correlations regardless of the level of a, as visualized by an upward slope in Figure 3c. Regarding weekly standard deviation (Figure 3c), the U-shaped relationship remains as in the daily level if the "initial" daily correlation is zero (the black line) or if the "initial" daily correlation and return spillover have the same sign (the left part of the red line and the right part of the blue line). However, if daily correlations and return spillovers have different signs, the trend of the relationship is unclear (the right part of the red line and the left part of the blue line).

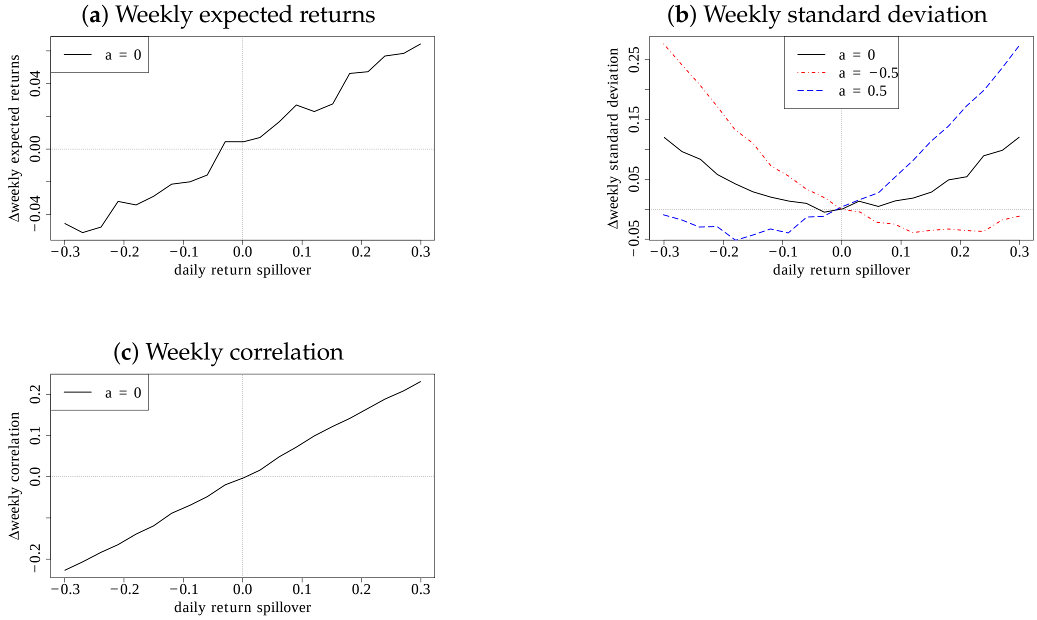


Figure 3. Effects of return spillovers on lower frequency assets' characteristics. This figure presents the effects of daily return spillovers on expected returns (**a**), standard deviation of the spillover-receiving asset (**b**), and the return correlation between spillover-giving and spillover-receiving assets (**c**) at weekly level. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. Because of overlaps between lines, we only present the case with $a = 0$ in (**a**,**c**). The graphs for $a = -0.5$ and $a = 0.5$ are qualitatively similar.

Why do such differences emerge when we aggregate higher frequencies to lower frequencies? We propose a simple framework in Figure 4 to explain the mechanisms of the observed relationships between daily return spillovers and assets' characteristics at the weekly level. First, we examine the positive link between daily return spillovers and weekly correlation. Consider the base case A1 in Panel A of Figure 4 where the daily contemporaneous correlation between X and Z is positive and there is no daily return spillovers between them. The corresponding paired case is A2 (A3) where the daily correlation is similar but there exists a positive (negative) return spillover from X to Z. Assuming that there is a positive shock to $x_{d,t}$ (return of asset X on day t), there would also be a positive shock to $z_{d,t}$ because of positive contemporaneous daily correlation. Meanwhile, a positive daily return spillover translates the initial shock into a positive shock to $z_{d,t+1}$ in the case A2. As a result, the weekly return of asset Z for this specific week increases when daily returns are aggregated into weekly frequencies. Consequently, compared to the base case A1, the increase of weekly returns of asset X is associated with a higher increase in return of asset Z in the case A2, leading to higher weekly correlation. On the contrary, a negative daily return spillover decreases the magnitude of the shock at the weekly level and decreases the weekly correlation between X and Z as can be seen in the case A3. Similar conclusions can be drawn from Panel B: negative (positive) daily return spillovers render daily negative correlations more (less) negative at weekly frequencies.

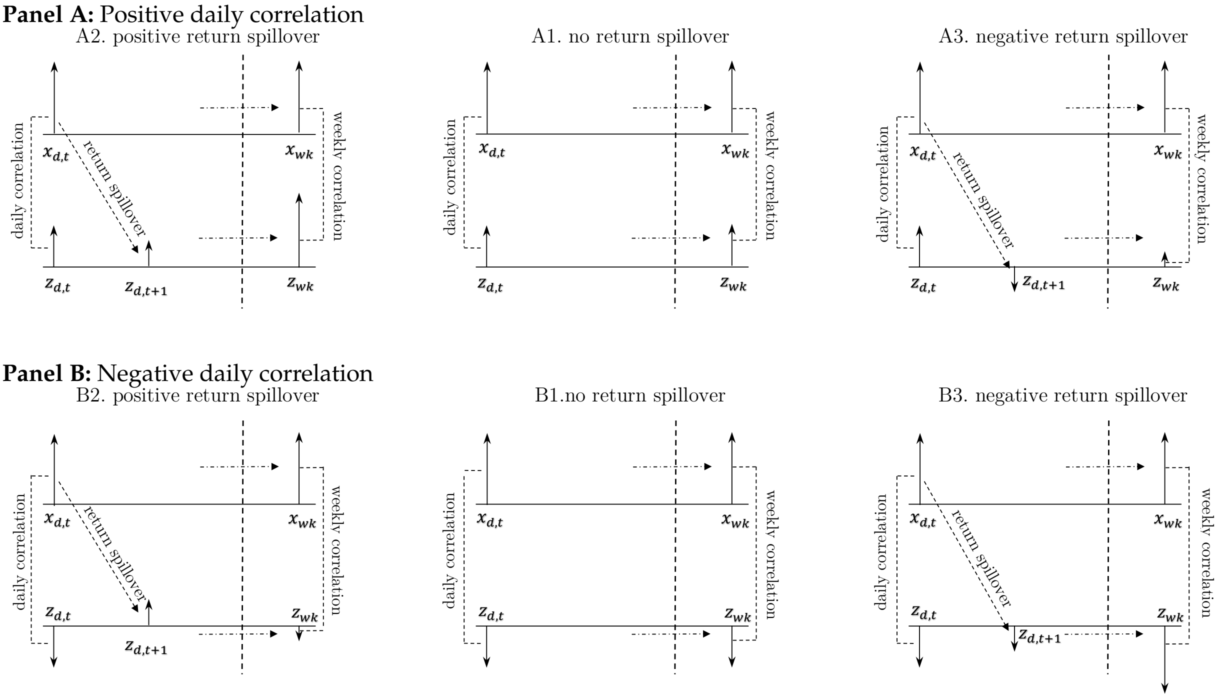


Figure 4. How return spillovers affects assets' return correlation. This figure illustrates the proposed channels through which return spillovers at daily frequency affect correlation at weekly frequency. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. For example, Panel A2 shows how a daily (d) return spillover from X to Z causes the weekly (wk) return of Z to increase (illustrated by a longer arrow) and thus leading to a higher co-movement of X and Z at the weekly level. The increased co-movement of X and Z (longer arrows of X and Z) can be seen by comparing A2 with the benchmark A1 (the no return spillovers case).

As the presence of daily return spillovers alters the magnitude of daily shocks and thus changes the magnitude of weekly returns of the spillover-receiving asset, its variance is also affected. More importantly, the effect should depend on the sign of the daily correlation. Specifically, when the daily correlation is positive as in Panel A of Figure 4, higher positive (negative) daily return spillovers lead to higher (lower) aggregated shocks at the weekly level and thus larger (smaller) weekly returns during that specific week. As a result, the volatility of weekly returns of the spillover-receiving asset increases (decreases). The opposing trend occurs in the case of negative daily correlation in Panel B of Figure 4. In a nutshell, it can be concluded that if daily return spillovers and daily correlations have the same sign, an increase in daily return spillovers (more positive/negative) would increase the spillover-receiving asset's variance at the weekly level and vice versa. Such mechanisms are visualized by links (a) and (b) in Figure 5. The link (c) in Figure 5 also depicts the link from daily return spillovers to weekly volatility through daily volatility, as described in Figure 1b. The channel (a) and channel (c) offset one another, resulting in the almost flat slope when daily correlation and daily return spillover have different signs as can be seen in the lower part of Figure 3b. However, it is likely that the effect of the channel (c) cannot completely counterbalance that of the channel (a), leading to stable negative differences in volatility for all level of return spillover. Meanwhile, when daily correlation and daily return spillovers have the same signs, channels (b) and (c) combined strengthen the effects (as illustrated in the upper part of Figure 3b).

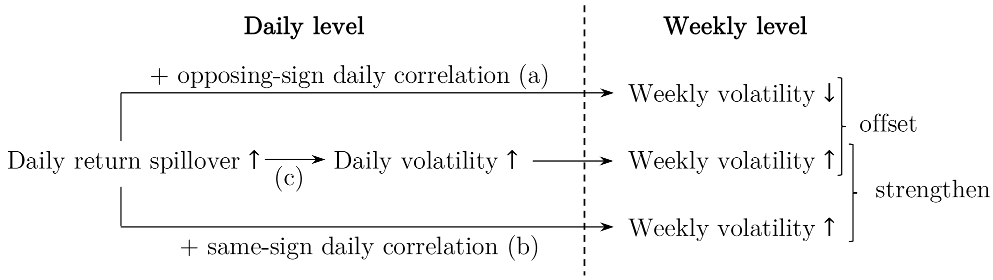


Figure 5. Channels of the links between daily return spillovers and asset's weekly volatility. This figure illustrates the relationship between return spillovers, volatility and correlations of assets at the daily level and their volatility at the weekly level. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies.

2.1.4. Return Frequencies and Portfolio Characteristics

The effects of daily return spillovers on the optimal portfolios formed by weekly returns are presented in Figure 6. The slope in Panel A1 is monotonically trending upward, indicating that if daily return spillovers are more positive (negative), the volatility of the minimum variance portfolio increases (decreases). The most likely driving force for this trend is the positive relationship between daily return spillovers and weekly correlations in Figure 3c. Specifically, more positive (negative) daily return spillovers drive weekly correlations closer to 1 (-1), which in turns shifts the efficient frontier to the right (left). As a result, the minimum variance increases (decreases). In addition, the increase in weekly volatility of the spillover-receiving asset as a result of the increase of daily return spillover when daily return spillover and daily correlation have the same sign could also be a driver shifting the efficient frontier to the right and increasing minimum variance.

The above-mentioned links between daily return spillovers and weekly volatility could also provide explanations for trends in Panel A2 of Figure 6. When daily correlations are zero (the black line) or have the same sign with daily return spillovers (the right part of the blue line and the left part of the red line), an increase in daily return spillovers (more positive/ negative) results in higher volatility of the spillover-receiving asset. Consequently, to maintain the minimum variance portfolio, less wealth should be allocated to that asset. Meanwhile, when daily return spillovers and daily correlations have different signs, lower volatility of the spillover-receiving asset force investors to invest more in it, leading to positive (but flat) differences observed in the upper part of Panel A2.

Regarding maximum Sharpe ratio portfolios, Panels B1 and B2 indicate that daily return spillovers positively affect the portfolio's Sharpe ratio and weight of the spillover-receiving asset, although the effects are not statistically significant for the former. Previous results (Figure 3a) showed that when daily return spillovers become more positive, weekly expected returns increase, shifting the efficient frontier upward and thus increasing the Sharpe ratio. However, the weekly correlation increasing towards one also shifts the efficient frontier to the right and thus decreases the Sharpe ratio. The counterbalance of two opposing effects results in insignificant differences of the maximum Sharpe ratio (Panel B1). Moreover, with higher expected returns investors should invest more in the spillover-receiving asset to maintain the maximum Sharpe ratio. The same explanation can be applied for the case of negative return spillovers. Note that although there could be a compensating effect from the volatility, it is likely completely offset by the expected returns effect, resulting in a monotonically increasing line in Panel B2.

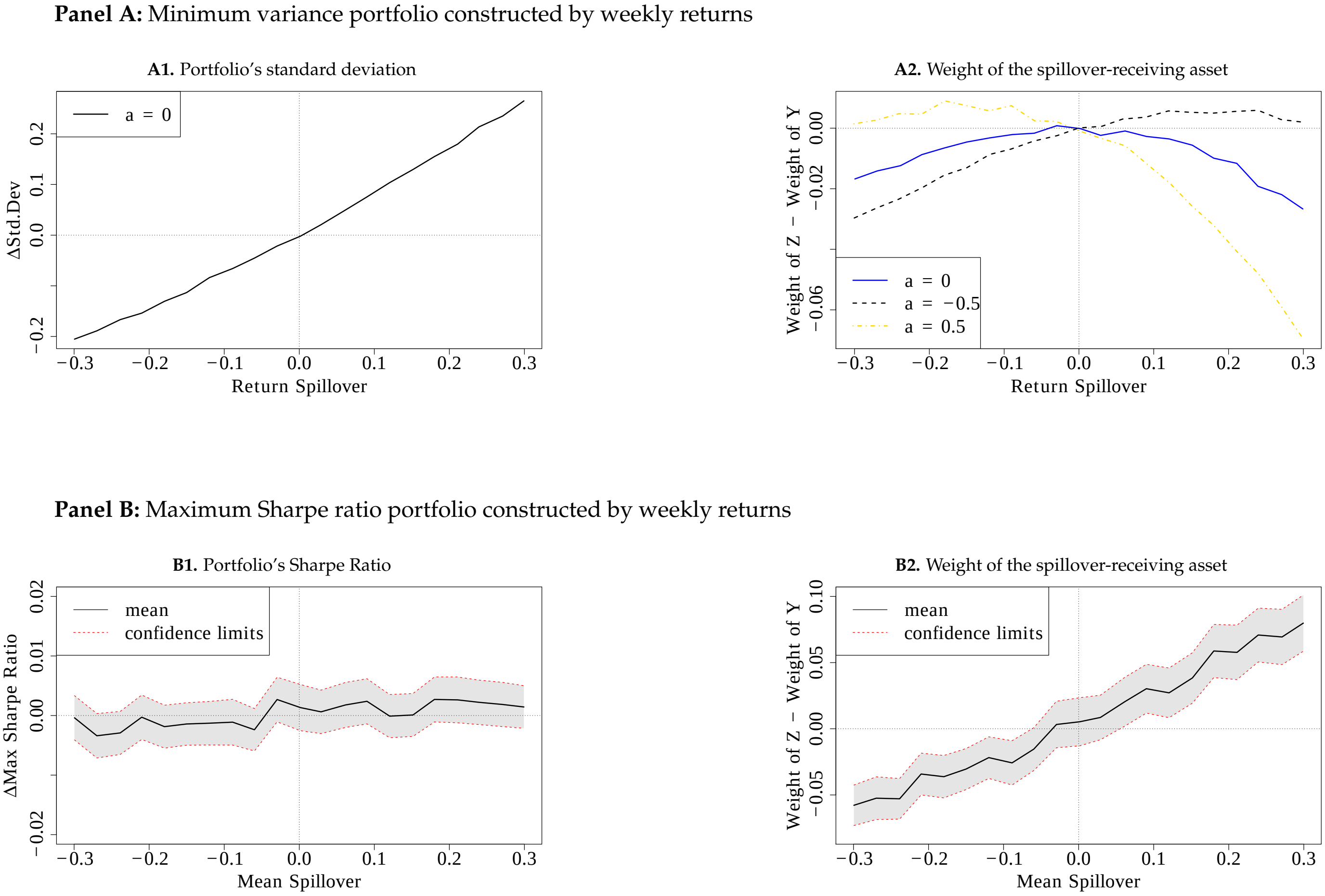


Figure 6. Return spillovers and portfolio optimization using lower frequency returns. This figure presents the differences in characteristics of optimal portfolios formed by weekly returns with and without daily returns spillover. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. Panel A presents the differences in the standard deviation and in the weight of the spillover-receiving asset in the minimum variance portfolios. Panel B presents the differences in the Sharpe ratio and in the weight of the spillover-receiving asset of the portfolios targeting maximum Sharpe ratio. Shaded areas represent confidence intervals. Confidence intervals in Panels A1 and A2 are not shown because they are very close to the mean. In all figures except A2, for brevity, we only present the graphs with a = 0. The graphs with a = −0.5 and a = 0.5 are similar.

2.2. Volatility Spillovers

Similar to the simulation design for return spillovers, we simulate two portfolios, one with and one without volatility spillovers, to examine how volatility spillovers affect assets characteristics and portfolio optimization. Return series with volatility spillovers are simulated using the GARCH (1,1) model (Bollerslev 1986; Engle 1982). Specifically, we first generate two random variables $\eta_{1,t}$ and $\eta_{2,t}$ that are drawn from a multivariate distribution with zero mean, unit variance and contemporaneous correlation a ($a \in \{-0.5,0,0.5\}$). Then, daily demeaned returns ($\varepsilon_{x,t}$, $\varepsilon_{y,t}$) and conditional volatility ($h_{x,t}$ and $h_{y,t}$) of assets X and Y without volatility spillovers are simulated as follows:

$$\begin{aligned} h_{x,t} &= \alpha_{01} + \alpha_{11}\varepsilon^2_{x,t-1} + \beta_{11}h_{x,t-1} \\ h_{y,t} &= \alpha_{02} + \alpha_{12}\varepsilon^2_{y,t-1} + \beta_{12}h_{y,t-1} \\ \varepsilon_{x,t} &= \eta_{1,t}\sqrt{h_{x,t}} \\ \varepsilon_{y,t} &= \eta_{2,t}\sqrt{h_{y,t}} \end{aligned} \tag{4}$$

The combination of X and Y forms a "non-spillover" portfolio, i.e., there is no spillovers between the portfolio constituents. In the same manner, we create a corresponding "spillover" portfolio that consists of the spillover-giving asset X and the spillover-receiving asset Z. The volatility spillover from X to Z is determined by a parameter $b \in [-0.1, 0.1]$:

$$\begin{aligned} h_{x,t} &= \alpha_{01} + \alpha_{11}\varepsilon^2_{x,t-1} + \beta_{11}h_{x,t-1} \\ h_{z,t} &= \alpha_{02} + \alpha_{12}\varepsilon^2_{z,t-1} + \beta_{12}h_{z,t-1} + bh_{x,t-1} \\ \varepsilon_{x,t} &= \eta_{1,t}\sqrt{h_{x,t}} \\ \varepsilon_{z,t} &= \eta_{2,t}\sqrt{h_{z,t}} \end{aligned} \tag{5}$$

For simulation Equations (4) and (5), we start the first observation with $h_{x,1} = h_{y,1} = h_{z,1} = 1$ and set $\alpha_{01} = \alpha_{02} = 0.01$, $\alpha_{11} = \alpha_{12} = 0.04$, and $\beta_{11} = \beta_{12} = 0.7$.[8] The daily return series of X, Y, and Z are based on the simulated demeaned returns $\varepsilon_{x,t}$, $\varepsilon_{y,t}$, and $\varepsilon_{z,t}$ plus the expected returns.[9] We then discard the first 100 observations in each return series. By design, the daily correlation between X and Y and between X and Z are similar as they are both determined by the correlation between $\eta_{1,t}$ and $\eta_{2,t}$ (parameter a). In addition, Y and Z share the same set of GARCH(1,1) parameters but there is only volatility spillover from X to Z but not to Y.

Thus, similar to the return spillovers case, the "non-spillover" portfolio $P_{0,d}(X,Y)$ is considered the base case, and all observed differences between $P_{0,d}$ and the "spillover" portfolio $P_{s,d}(X,Z)$ and equally between Y and Z are attributed to the spillover from X to Z.

2.2.1. Influence of Volatility Spillovers on Asset Characteristics

Applying a similar approach to that of return spillovers, we show in Figure 7 that volatility spillovers influence the variance of the spillover-receiving asset. The estimates are similar for both daily and weekly returns. The explanation is straightforward. If daily volatility spillovers increase, the spillover-receiving asset receives more variation from the source asset. Combined with its "own" variance, the resulting effect is an increase of observed variance at both daily and weekly frequencies. Meanwhile, volatility spillovers do not affect the expected returns or correlations unless we include a "volatility feedback" or volatility-in-mean effect in our simulation. In our main analysis, we assume variances and expected returns to be independent to clearly identify direct effects of spillovers on each variable.

2.2.2. Influence of Volatility Spillovers on Portfolio Characteristics

The effects of daily volatility spillovers on the optimal portfolio's characteristics are presented in Figure 8. Panel A1 shows that the more positive (negative) the daily volatility spillover is, the higher (lower) is the standard deviation of the minimum variance portfolio formed by daily returns. On the contrary, the more positive (negative) the daily volatility spillover is, the lower (higher) is the daily maximum Sharpe ratio (Panel B1). Regarding the optimal weights, Panel A2 and B2 show that if daily volatility spillovers become more positive (negative), investors should allocate less (more) wealth to the spillover-receiving asset to pursue either a minimum variance or a maximum Sharpe ratio portfolio. Very similar patterns are observed if portfolios are formed using weekly returns. These results are intuitive. If daily volatility spillovers increase, asset Z receives more variation from the source of the spillover (i.e., asset X). Combined with asset Z's "own" variance, the total effect is an increase of observed variance of asset Z at daily and weekly frequencies. As the increase in the variance of Z makes it riskier than X, it is reasonable that investors allocate less wealth to Z in order to minimize the portfolio's variance or maximize the portfolio's Sharpe ratio.

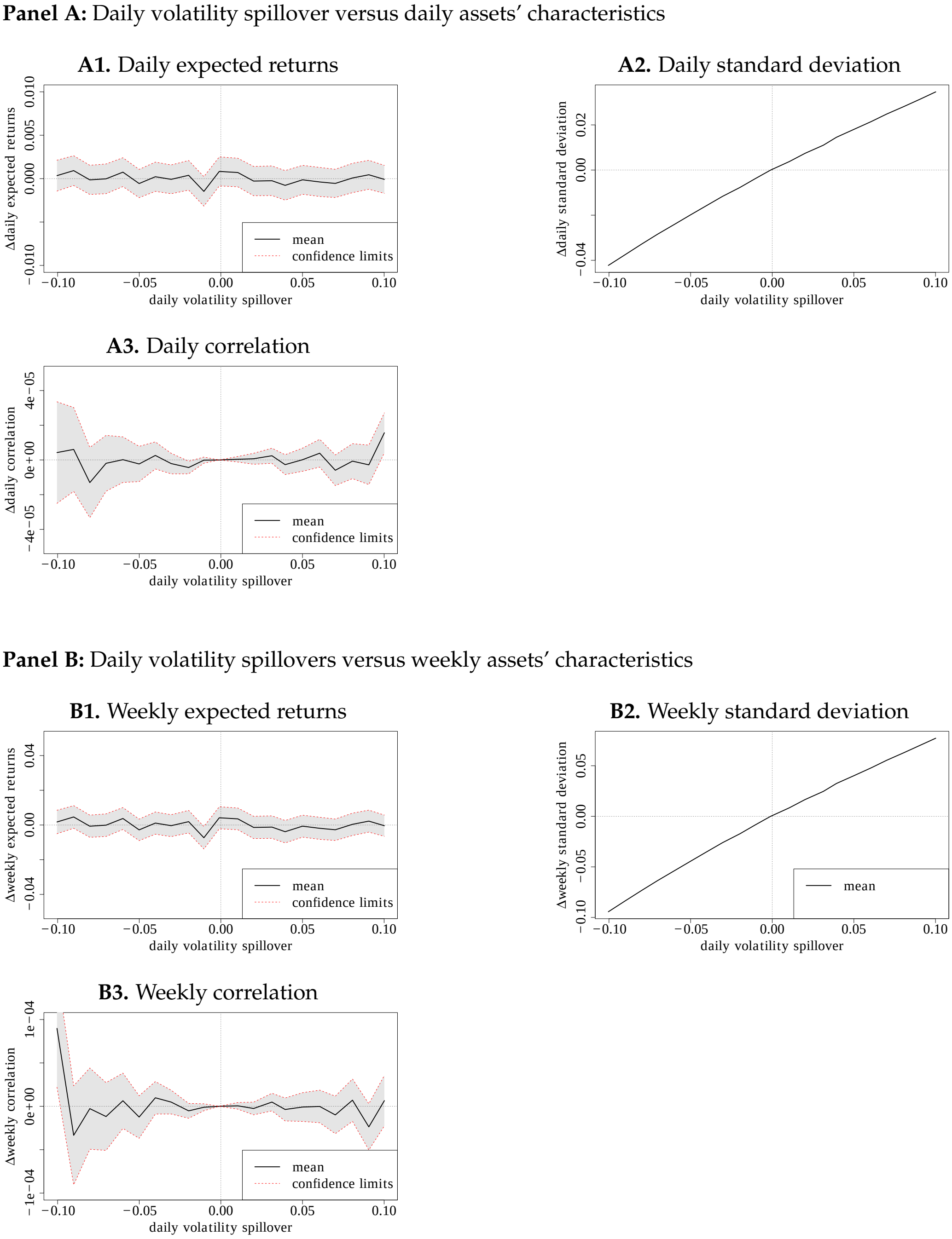
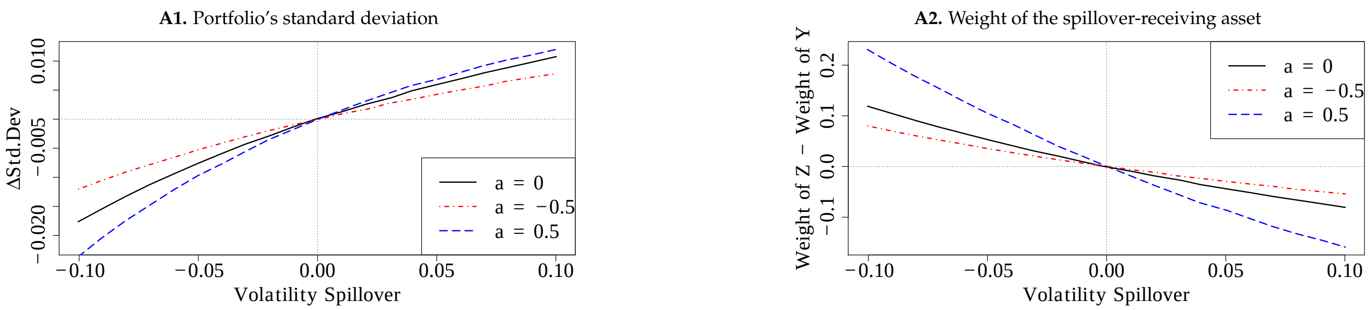
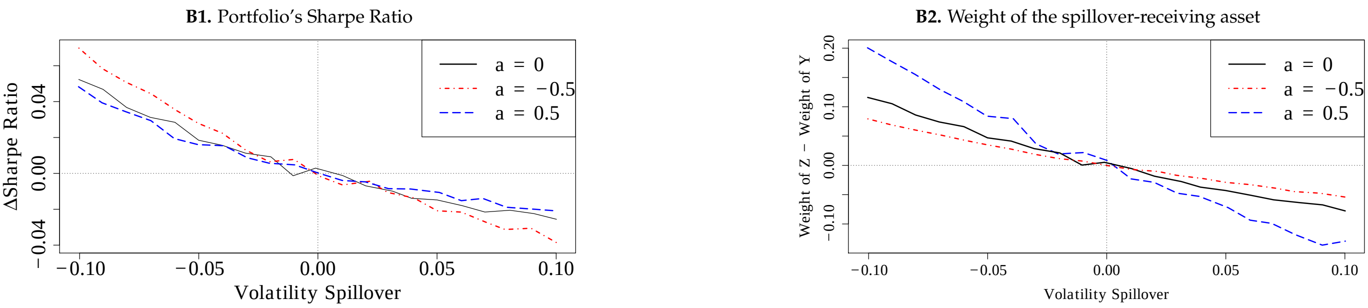


Figure 7. Effects of volatility spillovers on assets' characteristics. This figure presents the effects of daily volatility spillovers on the spillover-receiving asset's characteristics including expected returns, standard deviation and its correlation with the spillover-giving asset at daily frequency (**A**) and weekly frequency (**B**). We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. Because of overlaps between lines, for brevity we only present results for $a = 0$. The results for $a = -0.5$ and $a = 0.5$ are qualitatively similar.

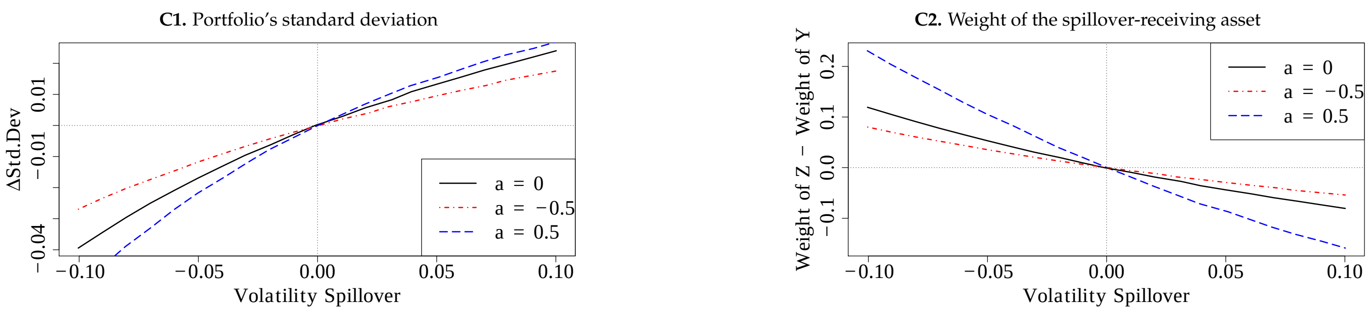
Panel A: Minimum variance portfolio constructed by daily returns



Panel B: Maximum Sharpe ratio portfolio constructed by daily returns



Panel C: Minimum variance portfolio constructed by week returns



Panel D: Maximum Sharpe ratio portfolio constructed by weekly returns

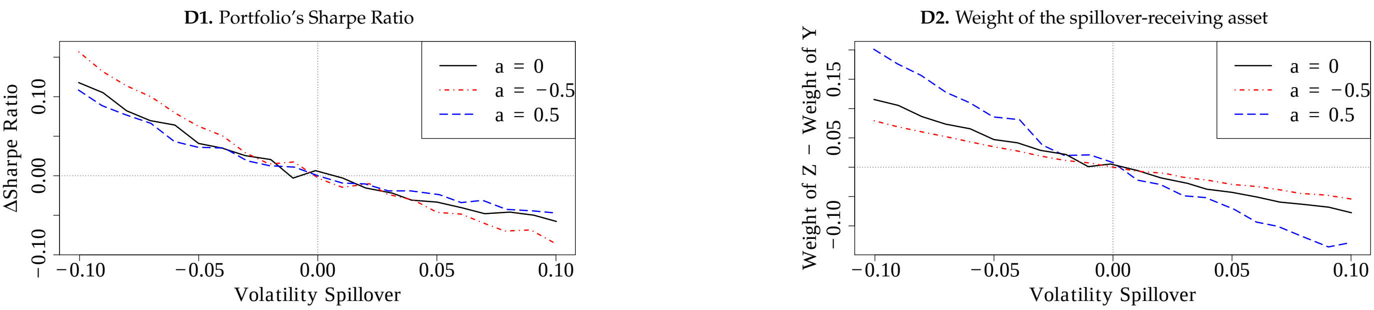


Figure 8. Volatility spillovers and portfolio optimization. This figure presents the differences in characteristics of portfolios formed by daily returns (**A**,**B**) or by weekly returns (**C**,**D**) with and without daily volatility spillover. Panels **A** and **C** present the differences in standard deviation and in the weight of the spillover-receiving asset in the minimum variance portfolios. Panels **B** and **D** present the differences in Sharpe ratio and in the weight of the spillover-receiving asset of the portfolio targeting maximum Sharpe ratio. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies.

Finally, Figure 9 summarizes the effects of return and volatility spillovers on the key asset characteristics and demonstrates that the effects of spillovers on portfolio formation and asset allocation are embedded in such characteristics. In the next section, we examine those proposed channels in a regression framework.

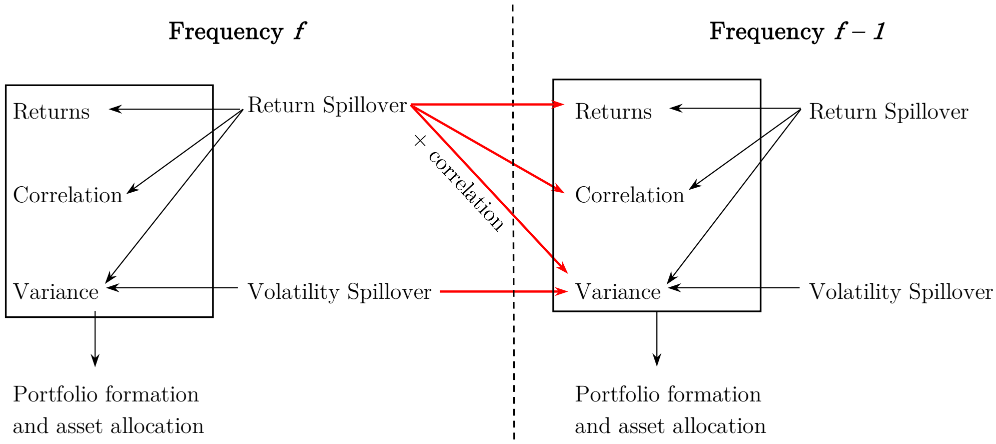


Figure 9. Channels of the links between spillovers and asset allocation. This figure illustrates that return spillovers affect expected returns, correlations and variances, while volatility spillovers affect variances, at both same frequency f and lower frequency $f-1$. The figure also demonstrates that spillovers are embedded in returns, correlations and variances rendering them redundant for portfolio formation and asset allocation. Volatility spillovers may affect returns and correlation through a volatility feedback effect but the primary link is through the variance.

2.3. Regression Analysis

In this section, we use regression models to examine the roles of return and volatility spillovers on portfolio characteristics controlling for typical portfolio construction ingredients such as expected returns, variances, and correlations. If the return and volatility spillovers only affect portfolio characteristics through the proposed channels in Figure 8, their estimated coefficients should be insignificant when controlling for those channels in a regression setting.

For return spillovers, similar to the univariate analysis, we employ Equation (3) to simulate daily return series of asset X ($x_{d,t}$) and asset Z ($Z_{d,t}$) with the correlation parameter a and the return spillovers parameter b randomly generated within $[-0.5, 0.5]$ and $[-0.03, 0.03]$, respectively. By construction, return and volatility spillovers are unidirectional from X to Z. For each regression, we generate 10,000 pairs (X, Z) corresponding with 10,000 observations. Other simulation settings are similar as described in Section 2.1.

Given the simulated daily return series, we use a regression framework to assess the impact of spillovers on characteristics of target portfolios, i.e., minimum variance and maximum Sharpe ratio, while controlling for possible channels. For each simulated pair $x_{d,t}$ and $Y_{d,t}$, we form minimum variance and maximum Sharpe ratio portfolios by using their estimated expected returns, variances and covariances.

Then, we run the following cross-sectional regressions:

$$Portf\_char_d = \alpha + \beta ret\_spill_d + \gamma Control_d + \varepsilon_d \tag{6}$$

where $Port\_char_d$ represents optimum portfolio's characteristics, which are either the standard deviation of the minimum variance portfolio ($MinVar_d$), the Sharpe ratio of the maximum Sharpe ratio portfolio ($MaxSharpe_d$), or the corresponding weights of the spillover-receiving asset Z in those portfolios ($WeightZ_{MV,d}$ and $WeightZ_{MS,d}$, respectively). $Control_d$ includes the set of standard variables, i.e., correlation ($corr_d$), standard deviations ($sd_{X,d}$ and $sd_{Z,d}$), and expected returns ($er_{X,d}$ and $er_{Z,d}$) of each asset X and Z. For lower frequency returns, we aggregate every five consecutive daily return observations to form weekly returns x_{wk} and z_{wk} and then run the regression Equation (7). Variables are defined similarly to Equation (6) but at weekly frequency except ret_spill_d which remains at daily frequency.

$$Portf\_char_{wk} = \alpha + \beta ret\_spill_d + \gamma Control_w k + \varepsilon_{wk} \tag{7}$$

Regarding volatility spillovers, we use Equation (5) to simulate two daily return series $x_{d,t}$ and $z_{d,t}$ and their corresponding conditional volatility h_x and h_z. The portfolio formation, weekly returns construction and regressions are conducted in a similar manner to those of return spillovers.

2.3.1. Relative Importance of Return Spillovers

Table 1 presents the regression results of model (6) with the dependent variables are $MinVar_d$ (Panel A) and $WeightZ_{MV,d}$ (Panel B). As the effects of return spillovers may be non-monotonic as shown earlier in this paper, we examine negative and positive return spillovers separately. Consistent with the graphical analysis in Figure 2 Panel A1, Table 1 Panel A shows that the coefficient estimates of ret_spill_d are negative (positive) when the value of ret_spill_d is negative (positive) and significant in the univariate regressions withn the minimum variance ($MinVar_d$) as the dependent variable. However, when we control for correlations, expected returns and variances of the portfolio's constituents, the magnitude of the coefficients of ret_spill_d decrease dramatically and become economically insignificant. For example, the estimated coefficient shrinks from -0.051 without any controls to -0.002 with controls. Furthermore, there is no difference in the Adjusted R^2 of the models with and without ret_spill_d, implying that given the constituents' correlation, expected returns and variances, return spillovers do not provide any additional explanation for the variance of the portfolio. Similar results are observed in the case that the weight of the spillover-receiving asset ($WeightZ_{MV,d}$) is the dependent variable in Panel B of Table 1.

Table 2 presents the effects of daily return spillovers on maximum Sharpe ratio portfolios formed by daily returns. Consistent with the graphical results in Panel B of Figure 2, all coefficients of ret_spill_d are positive and statistically significant in all univariate regressions. However, very small R^2 implies that the explanatory power of return spillovers on the maximum Sharpe ratio portfolio's characteristics are marginal. More importantly, when we control for the assets' correlations, expected returns, and variances, the magnitudes of coefficients of ret_spill_d are reduced to values very close to zero in both Panels A and B. Further, there are very little differences (always less than 0.1 percentage point) between the Adjusted R^2 of regressions with and without ret_spill_d. Thus, similar to the case based on the minimum variance portfolio, it can be concluded that the explanatory power of return spillovers on the maximum Sharpe ratio portfolio is trivial compared with other assets' characteristics.

Regression results of model (7) with portfolios formed by weekly returns are presented in Table 3. The sign and significance levels of coefficients of ret_spill_d in univariate regressions are consistent with the graphical univariate analysis in Figure 6. However, their magnitudes and statistical significance decrease noticeably after controlling for the assets' correlationS, expected returns and standard deviations. In addition, we also observe insignificant differences between Adjusted R^2 of regressions with and without ret_spill_d. Combined with the results from Tables 1 and 2, it can be concluded that the effects of return spillovers on optimal portfolios using either the same or lower frequency returns are fully captured by the input variables of portfolio optimization rendering spillovers less important.

Table 1. Effects of return spillovers on the minimum variance portfolio formed by the same frequency returns. This table presents the results from the regressions of the standard deviation (Panel A) and the weight of the spillover-receiving asset (Panel B) of the daily minimum variance portfolio on daily return spillover ($ret\_spill_{d,X\rightarrow Z}$), controlling for the daily correlation (cor_d), daily standard deviation, and expected returns of the spillover-giving asset X ($sd_{X,d}$ and $er_{X,d}$) and the spillover-receiving asset Z ($sd_{Z,d}$ and $er_{Z,d}$). We use "daily" for the illustration purpose; the results also apply to any other frequency. The last row in each Panel presents the difference between Adjusted R^2 of the full model and the restricted model without spillovers. Standard errors are in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: $MinVar_d$ as the Dependent Variable						
	Negative Return Spillover			*Positive Return Spillover*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ret\_spill_{d,X\rightarrow Z}$	−0.051 ***		−0.002 ***	0.069 ***		0.003 ***
	(0.009)		(0.0003)	(0.009)		(0.0003)
cor_d		0.457 ***	0.457 ***		0.457 ***	0.457 ***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
$sd_{X,d}$		0.344 ***	0.346 ***		0.345 ***	0.349 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{Z,d}$		0.336 ***	0.333 ***		0.337 ***	0.333 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{X,d}$		−0.0003	−0.0003		−0.001	−0.0004
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{Z,d}$		−0.001 *	−0.001		0.001	−0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.869 ***	0.032 ***	0.033 ***	0.866 ***	0.030 ***	0.031 ***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Adjusted R^2	0.007	0.999	0.999	0.013	0.999	0.999
Δ Adjusted R^2		0.000			0.000	
Panel B: $WeightZ_{MV,d}$ as the Dependent Variable						
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$ret\_spill_{d,X\rightarrow Z}$	0.074 ***		−0.001 ***	−0.078 ***		0.001 ***
	(0.002)		(0.0002)	(0.002)		(0.0003)
cor_d		−0.007 ***	−0.007 ***		−0.008 ***	−0.008 ***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
$sd_{X,d}$		0.408 ***	0.408 ***		0.408 ***	0.409 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{Z,d}$		−0.404 ***	−0.405 ***		−0.403 ***	−0.404 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{X,d}$		−0.001	−0.001		−0.001	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{Z,d}$		0.002 **	0.002 ***		0.0002	−0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.504 ***	0.496 ***	0.496 ***	0.505 ***	0.494 ***	0.494 ***
	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)
Adjusted R^2	0.243	0.990	0.990	0.276	0.990	0.990
Δ Adjusted R^2		0.000			0.000	

Table 2. Effects of return spillovers on the maximum Sharpe ratio portfolio formed by the same frequency returns. This table presents the results from the regression of the Sharpe ratio (Panel A) and the weight of the spillover-receiving asset (Panel B) of the daily maximum Sharpe ratio portfolio on the daily return spillovers ($ret\_spill_{d,X \to Z}$), controlling for daily correlation (cor_d), daily standard deviation and expected returns of the spillover-giving asset X ($sd_{X,d}$ and $er_{X,d}$) and the spillover-receiving asset Z ($sd_{Z,d}$ and $er_{Z,d}$). We use "daily" for the illustration purpose; the results also apply to any other frequency. The last row in each Panel presents the differences between Adjusted R^2 of the full model and the restricted model without spillovers. Standard errors are in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: $MaxSharpe_d$ as the Dependent Variable						
	Negative Return Spillover			*Positive Return Spillover*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ret\_spill_{d,X \to Z}$	0.025 ***		−0.002 ***	0.028 ***		−0.004 ***
	(0.003)		(0.001)	(0.004)		(0.001)
cor_d		−0.027 ***	−0.027 ***		−0.034 ***	−0.034 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{X,d}$		−0.027 ***	−0.024 ***		−0.017 ***	−0.022 ***
		(0.002)	(0.003)		(0.002)	(0.002)
$sd_{Z,d}$		−0.018 ***	−0.022 ***		−0.034 ***	−0.028 ***
		(0.002)	(0.003)		(0.002)	(0.002)
$er_{X,d}$		0.592 ***	0.592 ***		0.529 ***	0.529 ***
		(0.003)	(0.003)		(0.002)	(0.002)
$er_{Z,d}$		0.525 ***	0.526 ***		0.582 ***	0.583 ***
		(0.003)	(0.003)		(0.002)	(0.002)
Constant	0.070 ***	0.053 ***	0.054 ***	0.072 ***	0.060 ***	0.060 ***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Adjusted R^2	0.011	0.944	0.944	0.011	0.972	0.973
Δ Adjusted R^2		0.000			0.001	
Panel B: $WeightZ_{MS,d}$ as the Dependent Variable						
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$ret\_spill_{d,X \to Z}$	0.310 ***		−0.004	0.141 ***		−0.013
	(0.032)		(0.015)	(0.026)		(0.012)
cor_d		−0.073 ***	−0.073 ***		0.060 ***	0.060 ***
		(0.011)	(0.011)		(0.009)	(0.009)
$sd_{X,d}$		0.396 ***	0.391 ***		0.435 ***	0.420 ***
		(0.042)	(0.038)		(0.031)	(0.035)
$sd_{Z,d}$		−0.421 ***	−0.415 ***		−0.419 ***	−0.401 ***
		(0.041)	(0.035)		(0.029)	(0.034)
$er_{X,d}$		−4.471 ***	−4.472 ***		−4.454 ***	−4.455 ***
		(0.042)	(0.042)		(0.034)	(0.034)
$er_{Z,d}$		5.048 ***	5.047 ***		3.809 ***	3.815 ***
		(0.043)	(0.042)		(0.033)	(0.033)
Constant	0.500 ***	0.494 ***	0.494 ***	0.512 ***	0.528 ***	0.525 ***
	(0.006)	(0.030)	(0.030)	(0.005)	(0.025)	(0.025)
Adjusted R^2	0.018	0.857	0.857	0.006	0.840	0.840
Δ Adjusted R^2		0.000			0.000	

Table 3. Effects of return spillovers on optimal portfolios formed by lower frequency returns. This table presents the results from the regression of the weekly optimal portfolio characteristics on the daily return spillovers ($ret\_spill_{d,X \to Z}$. Portfolio characteristics include the standard deviation of the minimum variance portfolio (Panel A), the Sharpe ratio of the maximum Sharpe ratio portfolio (Panel C), and corresponding weights of the spillover-receiving asset in such portfolios (Panels B and D). We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. Control variables include weekly correlation (cor_{wk}), weekly standard deviation and expected returns of the spillover-giving asset X ($sd_{X,wk}$ and $er_{X,wk}$) and the spillover-receiving Z ($sd_{Z,wk}$ and $er_{Z,wk}$). The last row in each Panel presents the difference between Adjusted R^2 of the full model and the restricted model without spillovers. Standard errors are in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: $MinVar_{wk}$ as the Dependent Variable						
	Negative Return Spillover			*Positive Return Spillover*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ret\_spill_{d,X \to Z}$	0.703 ***		−0.024 ***	0.862 ***		−0.020 ***
	(0.021)		(0.002)	(0.022)		(0.001)
cor_{wk}		1.067 ***	1.076 ***		0.957 ***	0.964 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{X,wk}$		0.326 ***	0.327 ***		0.380 ***	0.379 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{Z,wk}$		0.306 ***	0.304 ***		0.353 ***	0.354 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{X,wk}$		−0.001	−0.0005		−0.0004	−0.001
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{Z,wk}$		−0.004 ***	−0.003 **		−0.0004	0.001 *
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	1.942 ***	0.211 ***	0.210 ***	1.938 ***	−0.077 ***	−0.077 ***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
Adjusted R^2	0.188	0.996	0.996	0.226	0.998	0.998
Δ Adjusted R^2		0.000			0.000	
Panel B: $WeightZ_{MV,wk}$ as the Dependent Variable						
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$ret\_spill_{d,X \to Z}$	0.062 ***		−0.001 **	−0.106 ***		−0.002 ***
	(0.004)		(0.001)	(0.005)		(0.001)
cor_{wk}		−0.007 ***	−0.007 ***		−0.012 ***	−0.011 ***
		(0.0004)	(0.0004)		(0.001)	(0.001)
$sd_{X,wk}$		0.165 ***	0.165 ***		0.206 ***	0.206 ***
		(0.0004)	(0.0004)		(0.001)	(0.001)
$sd_{Z,wk}$		−0.159 ***	−0.160 ***		−0.212 ***	−0.212 ***
		(0.0003)	(0.0003)		(0.0005)	(0.0005)
$er_{X,wk}$		0.0001	0.0001		−0.001 ***	−0.001 ***
		(0.0003)	(0.0003)		(0.0005)	(0.0005)
$er_{Z,wk}$		0.001 **	0.001 ***		0.0002	0.0004
		(0.0003)	(0.0003)		(0.0004)	(0.0004)
Constant	0.504 ***	0.483 ***	0.483 ***	0.507 ***	0.516 ***	0.516 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.050	0.984	0.984	0.085	0.982	0.982
Δ Adjusted R^2		0.000			0.000	

Table 3. *Cont.*

Panel C: $MaxSharpe_{wk}$ as the Dependent Variable						
	Negative Return Spillover			*Positive Return Spillover*		
	(13)	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
$ret\_spill_{d,X \rightarrow Z}$	0.002		−0.004 **	0.015 *		−0.004 *
	(0.008)		(0.002)	(0.008)		(0.002)
cor_{wk}		−0.077 ***	−0.076 ***		−0.065 ***	−0.064 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{X,wk}$		−0.028 ***	−0.028 ***		−0.021 ***	−0.022 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$sd_{Z,wk}$		−0.021 ***	−0.022 ***		−0.029 ***	−0.028 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{X,wk}$		0.279 ***	0.279 ***		0.218 ***	0.218 ***
		(0.001)	(0.001)		(0.001)	(0.001)
$er_{Z,wk}$		0.254 ***	0.255 ***		0.249 ***	0.250 ***
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.158 ***	0.120 ***	0.119 ***	0.161 ***	0.143 ***	0.143 ***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Adjusted R^2	−0.0002	0.957	0.957	0.0005	0.956	0.956
Δ Adjusted R^2		0.000			0.000	
Panel D: WeightZ$_{MS,wk}$ as the Dependent Variable						
	(19)	**(20)**	**(21)**	**(22)**	**(23)**	**(24)**
$ret\_spill_{d,X \rightarrow Z}$	0.211 ***		0.003	0.266 ***		−0.014
	(0.026)		(0.013)	(0.033)		(0.017)
cor_{wk}		−0.056 ***	−0.057 ***		0.081 ***	0.086 ***
		(0.008)	(0.009)		(0.011)	(0.012)
$sd_{X,wk}$		0.147 ***	0.146 ***		0.193 ***	0.193 ***
		(0.008)	(0.008)		(0.010)	(0.010)
$sd_{Z,wk}$		−0.150 ***	−0.150 ***		−0.179 ***	−0.178 ***
		(0.007)	(0.007)		(0.010)	(0.010)
$er_{X,wk}$		−0.712 ***	−0.712 ***		−1.142 ***	−1.142 ***
		(0.007)	(0.007)		(0.009)	(0.009)
$er_{Z,wk}$		0.800 ***	0.800 ***		0.970 ***	0.971 ***
		(0.007)	(0.007)		(0.009)	(0.009)
Constant	0.497 ***	0.477 ***	0.477 ***	0.506 ***	0.516 ***	0.515 ***
	(0.004)	(0.022)	(0.022)	(0.006)	(0.029)	(0.029)
Adjusted R^2	0.013	0.840	0.840	0.012	0.826	0.826
Δ Adjusted R^2		0.000			0.000	

2.3.2. Relative Importance of Volatility Spillovers

The regression results of the effects of volatility spillovers on portfolio optimization are presented in Table 4. The minimum variance and maximum Sharpe ratio portfolios and the daily and weekly results from univariate regressions are all consistent with the graphical results in Figure 8 as the coefficients of vol_spill_d are positive (negative) in regressions with minimum variance (maximum) Sharpe ratio as the dependent variable, and all negative in regressions using the weight of the spillover-receiving asset as the dependent variable. However, when we control for the portfolio's constituents' characteristics, including correlation, expected returns, and variances, similar to the return spillovers case, not only the coefficients' magnitudes of vol_spill_d fall, but also their statistical significance. Another interesting point is that adjusted R^2 of regressions with and without volatility spillovers are indifferent implying that there is no additional explanatory power of volatility spillovers over the portfolios' characteristics. This evidence supports the notion that volatility spillovers have very little influence on asset allocation compared with other assets' characteristics including correlation, variances and expected returns, and effects of the former, if they exist, are channeled through the latter.

Table 4. Effects of volatility spillovers on optimal portfolios. This table presents the results from the regression on daily volatility spillovers (vol_spill_d) with dependent variables are either the standard deviation of the portfolio targeting minimum variance, the Sharpe ratio of the portfolio targeting maximum Sharpe ratio, or the corresponding weight of the spillover-receiving asset in such optimum portfolios. Portfolios are formed by either daily or weekly returns. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies. The last row in each Panel presents the difference between Adjusted R^2 of the full model and the restricted model without spillover. Standard errors are in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: Effects of Daily Volatility Spillovers on Daily Minimum Variance Portfolio						
	Portfolio's Standard Deviation			*Weight of the Spillover-Receiving Asset*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
vol_spill_d	0.129 ***		−0.006 ***	−0.987 ***		0.046 ***
	(0.003)		(0.001)	(0.005)		(0.012)
cor_{wk}		0.070 ***	0.070 ***		0.008 ***	0.008 ***
		(0.0001)	(0.0001)		(0.001)	(0.001)
$sd_{X,wk}$		0.315 ***	0.318 ***		2.858 ***	2.840 ***
		(0.024)	(0.024)		(0.242)	(0.242)
$sd_{Z,wk}$		0.361 ***	0.376 ***		−2.825 ***	−2.946 ***
		(0.001)	(0.003)		(0.009)	(0.033)
$er_{X,wk}$		0.001	0.001		−0.003	−0.003
		(0.001)	(0.001)		(0.014)	(0.014)
$er_{Z,wk}$		0.00001	−0.00002		0.002	0.002
		(0.001)	(0.001)		(0.014)	(0.014)
Constant	0.136 ***	0.004	0.0004	0.507 ***	0.497 ***	0.524 ***
	(0.0002)	(0.005)	(0.005)	(0.0003)	(0.048)	(0.048)
Adjusted R^2	0.124	0.991	0.991	0.827	0.905	0.905
Δ Adjusted R^2		0.000			0.000	

Panel B: Effects of Daily Volatility Spillovers on Daily Maximum Sharpe Ratio Portfolio						
	Portfolio's Sharpe Ratio			*Weight of the Spillover-Receiving Asset*		
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
vol_spill_d	−0.348 ***		0.012	−0.911 ***		0.095 *
	(0.016)		(0.014)	(0.026)		(0.049)
cor_{wk}		−0.180 ***	−0.180 ***		0.011 ***	0.011 ***
		(0.001)	(0.001)		(0.003)	(0.003)
$sd_{wk,X}$		−0.947 ***	−0.951 ***		4.246 ***	4.208 ***
		(0.288)	(0.288)		(0.980)	(0.980)
$sd_{wk,Z}$		−1.015 ***	−1.046 ***		−2.634 ***	−2.885 ***
		(0.011)	(0.039)		(0.037)	(0.134)
$er_{wk,X}$		3.662 ***	3.662 ***		−6.217 ***	−6.217 ***
		(0.016)	(0.016)		(0.056)	(0.056)
$er_{wk,Z}$		3.805 ***	3.805 ***		6.126 ***	6.127 ***
		(0.016)	(0.016)		(0.056)	(0.056)
Constant	0.372 ***	0.344 ***	0.351 ***	0.506 ***	0.193	0.250
	(0.001)	(0.057)	(0.057)	(0.002)	(0.192)	(0.195)
Adjusted R^2	0.046	0.940	0.940	0.113	0.749	0.749
Δ Adjusted R^2		0.000			0.000	

Table 4. *Cont.*

Panel C: Effects of Daily Volatility Spillovers on Weekly Minimum Variance Portfolio						
	Portfolio's Standard Deviation			*Weight of the Spillover-Receiving Asset*		
	(13)	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
vol_spill_d	0.286 ***		0.007 ***	−0.990 ***		−0.002
	(0.008)		(0.002)	(0.006)		(0.009)
cor_{wk}		0.155 ***	0.155 ***		0.008 ***	0.008 ***
		(0.0002)	(0.0002)		(0.001)	(0.001)
$sd_{X,wk}$		0.330 ***	0.331 ***		1.237 ***	1.237 ***
		(0.003)	(0.003)		(0.015)	(0.015)
$sd_{Z,wk}$		0.358 ***	0.351 ***		−1.262 ***	−1.260 ***
		(0.001)	(0.003)		(0.004)	(0.011)
$er_{X,wk}$		0.001	0.001		0.0004	0.0004
		(0.001)	(0.001)		(0.003)	(0.003)
$er_{Z,wk}$		−0.0003	−0.0003		−0.0004	−0.0004
		(0.001)	(0.001)		(0.003)	(0.003)
Constant	0.303 ***	0.003	0.006 ***	0.507 ***	0.514 ***	0.513 ***
	(0.0005)	(0.002)	(0.002)	(0.0004)	(0.007)	(0.008)
Adjusted R^2	0.118	0.990	0.990	0.719	0.904	0.904
Δ Adjusted R^2		0.000			0.000	
Panel D: Effects of Daily Volatility Spillovers on Weekly Maximum Sharpe Ratio Portfolio						
	Portfolio's Sharpe Ratio			*Weight of the Spillover-Receiving Asset*		
	(19)	**(20)**	**(21)**	**(22)**	**(23)**	**(24)**
vol_spill_d	−0.779 ***		−0.061 **	−0.913 ***		0.033
	(0.036)		(0.024)	(0.026)		(0.036)
cor_{wk}		−0.404 ***	−0.404 ***		0.010 ***	0.010 ***
		(0.002)	(0.002)		(0.003)	(0.003)
$sd_{X,wk}$		−0.847 ***	−0.851 ***		1.079 ***	1.081 ***
		(0.038)	(0.038)		(0.058)	(0.058)
$sd_{Z,wk}$		−1.007 ***	−0.940 ***		−1.177 ***	−1.213 ***
		(0.011)	(0.028)		(0.016)	(0.042)
$er_{X,wk}$		1.642 ***	1.642 ***		−1.245 ***	−1.245 ***
		(0.008)	(0.008)		(0.011)	(0.011)
$er_{Z,wk}$		1.706 ***	1.706 ***		1.229 ***	1.229 ***
		(0.008)	(0.008)		(0.011)	(0.011)
Constant	0.834 ***	0.721 ***	0.694 ***	0.506 ***	0.552 ***	0.567 ***
	(0.002)	(0.018)	(0.021)	(0.002)	(0.027)	(0.031)
Adjusted R^2	0.045	0.937	0.937	0.110	0.746	0.746
Δ Adjusted R^2		0.000			0.000	

2.4. Diebold–Yilmaz Spillover Index

The simulation results so far rely on estimated coefficients of a VAR(1) model to measure spillovers. This section presents some robustness tests on whether spillovers are embedded in assets' correlations, expected returns and variances based on the widely-used Diebold and Yilmaz (2009) spillover index. Analogous to the previous design, we generate "spillover" pair (X,Z) and "non-spillover" pair (X,Y) using Equations (2) and (3) for return spillovers and Equations (4) and (5) for volatility spillovers. Then we calculate the difference in the Diebold–Yilmaz spillover indices of (X,Z) and (X,Y) and compare it with the differences in contemporaneous correlations, expected returns and variances of assets at both same frequency (i.e., daily) and lower frequency (i.e., weekly). We repeat the process 1000 times, each with a random return spillover parameter in [−0.3,0.3] and a random volatility spillover parameter in $[-0.1, 0.1]$.[10] As the Diebold–Yilmaz spillover index only reflects the magnitude of the overall spillover level, and thus is always positive, we multiply the index with -1 if the spillover parameter b is negative to capture the sign of the spillover.

The results in Figure 10 are fully consistent with the findings above. Panel B shows that there is a highly significant positive relationship of weekly correlations with the daily spillover index. This result supports one of our main findings that higher-frequency return spillovers are embedded in lower-frequency correlations. We do not observe a significant relation between the daily spillover index and daily correlations (see Panel A), which is consistent with the black line in Figure 1c, because we randomly draw the "initial" correlation parameter a in $[-0.5, 0.5]$, resulting in a zero average.[11]

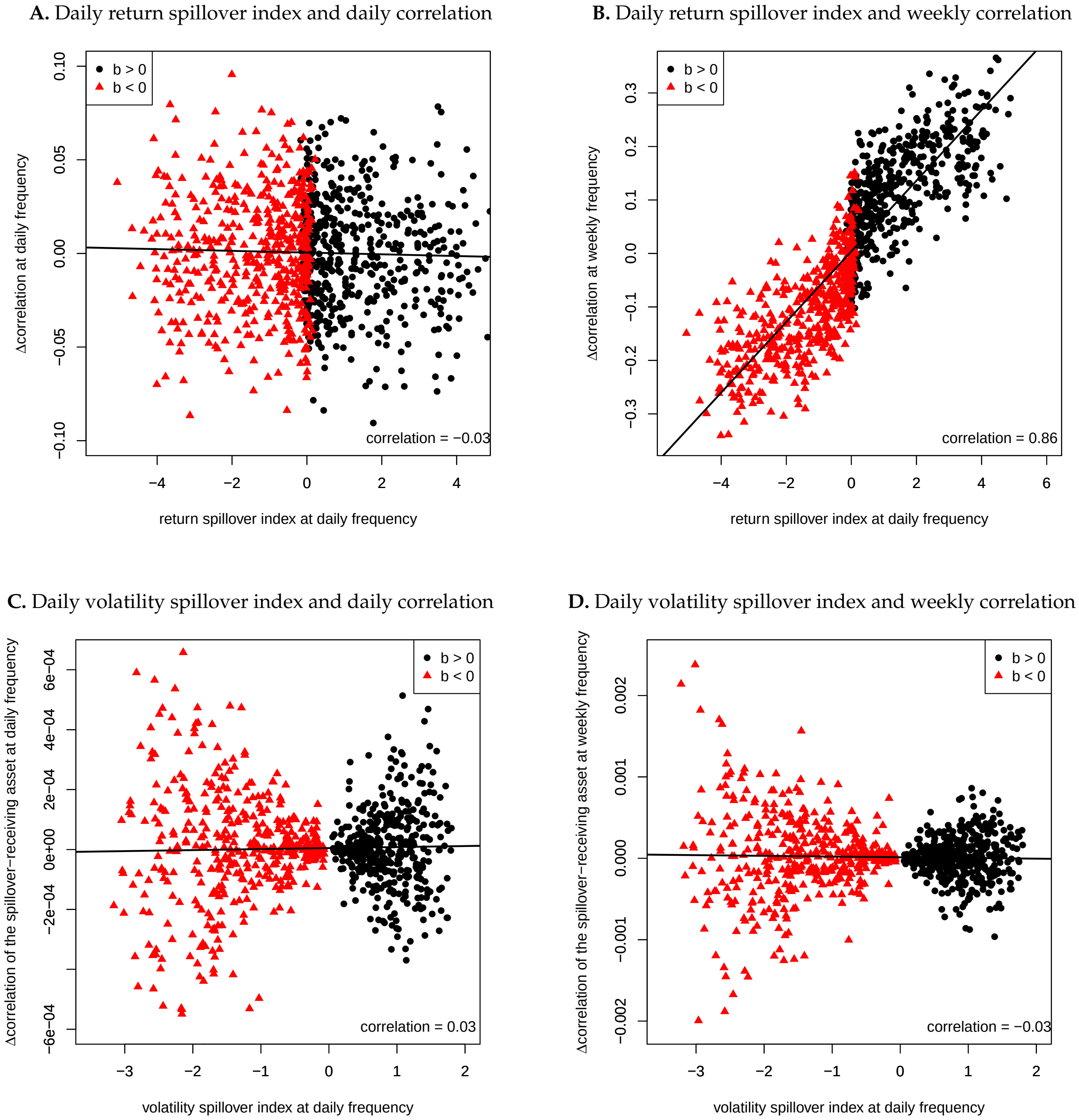


Figure 10. *Cont.*

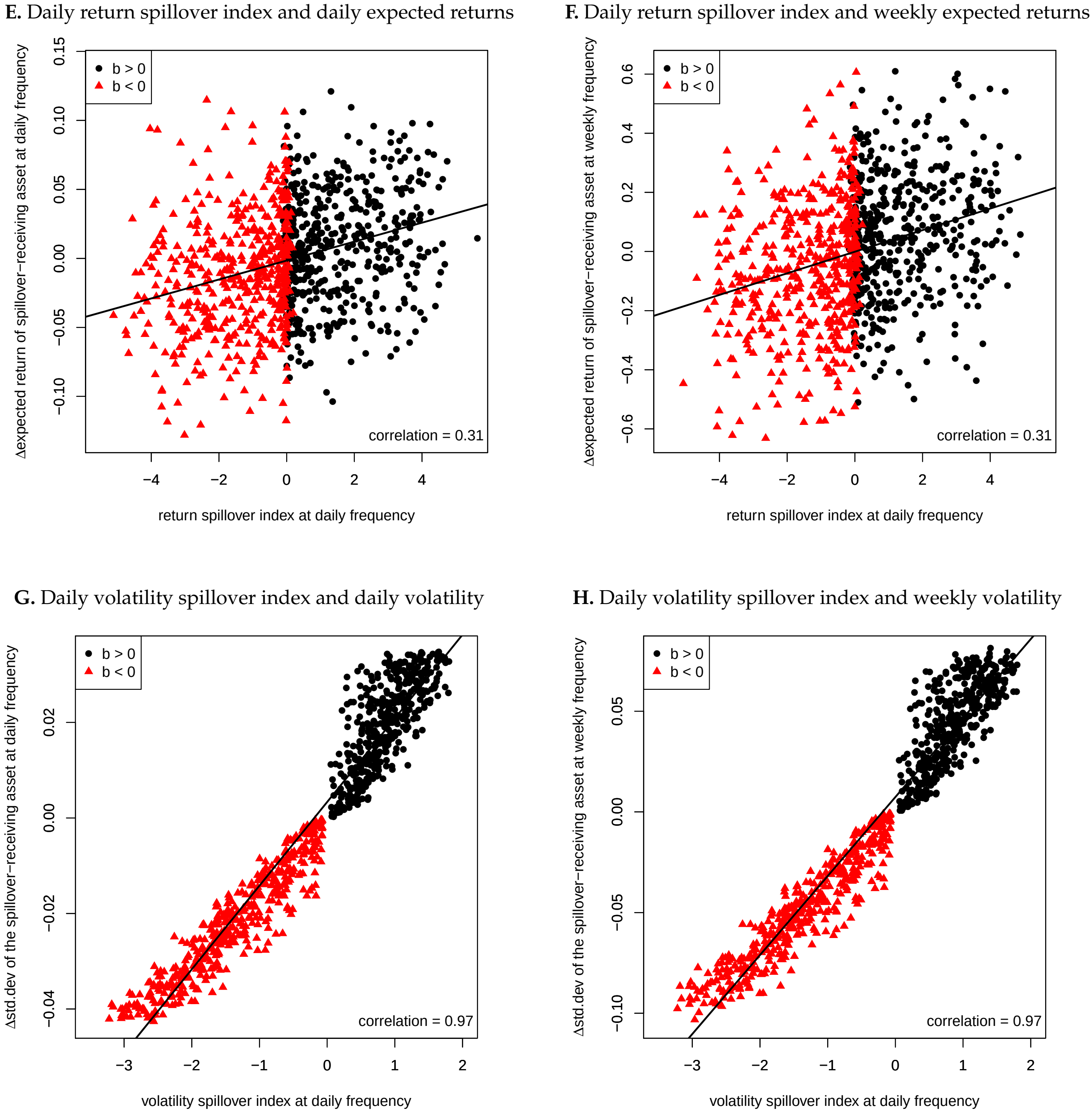


Figure 10. Simulation results with the Diebold–Yilmaz spillover index. This figure presents the effects of daily spillovers (measured by the Diebold–Yilmaz spillover index) on assets' characteristic at daily and weekly frequencies. We use "daily" and "weekly" for the illustration purpose; the results also apply to other relative "high" and "low" frequencies.

We also observe a positive relation between the return spillover and the expected returns at both same and lower frequencies in Panel E and F confirming that return spillovers are embedded in expected returns consistent with Figure 1a.

Regarding volatility spillovers, Panels C and D of Figure 10 show that volatility spillovers do not affect correlations, which is similar to Figure 7 (Panel A2 and B2). In contrast, there is a strong positive relationship between the daily volatility spillover index and both daily and weekly volatility of Z (Panel G and H). These results, again, support our hypothesis and findings that volatility spillovers are embedded in volatility of the spillover-receiving assets at both same and lower frequencies.

2.5. Multi-Asset Portfolios

We simulate 20 assets with multidirectional return spillovers using a full VAR(1) model and construct an optimal 20-asset portfolio either targeting minimum variance or maximum Sharpe ratio.[12] We repeat the process 10,000 times to obtain 10,000 observations of optimal portfolio characteristics (minimum variance, maximum Sharpe ratio, and constituents' weights) and asset characteristics (spillovers, correlations, expected returns, and standard deviations) at both daily and weekly levels. We repeat the process with multi-directional volatility spillovers using a GARCH(1,1) model. Then, analogous to the approach described in Section 2.3, we compare the Adjusted R^2 of the following unrestricted model:

$$\begin{aligned} Portf\_char = & \alpha + \beta_1 \sum_{i=1}^{20} \sum_{j=1}^{20} ret\_spill_{i \to j} + \\ & + \beta_2 \sum_{i=1}^{19} \sum_{j=i+1}^{20} cor_{i,j} + \beta_3 \sum_{i=1}^{20} sd_i + \beta_4 \sum_{i=1}^{20} er_i + \varepsilon \end{aligned} \tag{8}$$

with the Adjusted R^2 of the restricted model excluding the spillover effects ($\beta_1 = 0$). The difference in Adjusted R^2 (ΔAdj.R^2) reflects the marginal contributions of spillovers in explaining the optimal portfolios' characteristics. Figure 11 presents the histograms of ΔAdj.R^2 of all regression models with daily and weekly portfolio characteristics as dependent variables. Similar to Tables 1–4 for two-asset portfolios, the ΔAdj.R^2s are close to zero, indicating that given the contemporaneous correlation, expected returns and standard deviations estimates, both return and volatility spillovers provide very little additional information for investors in asset allocation process.

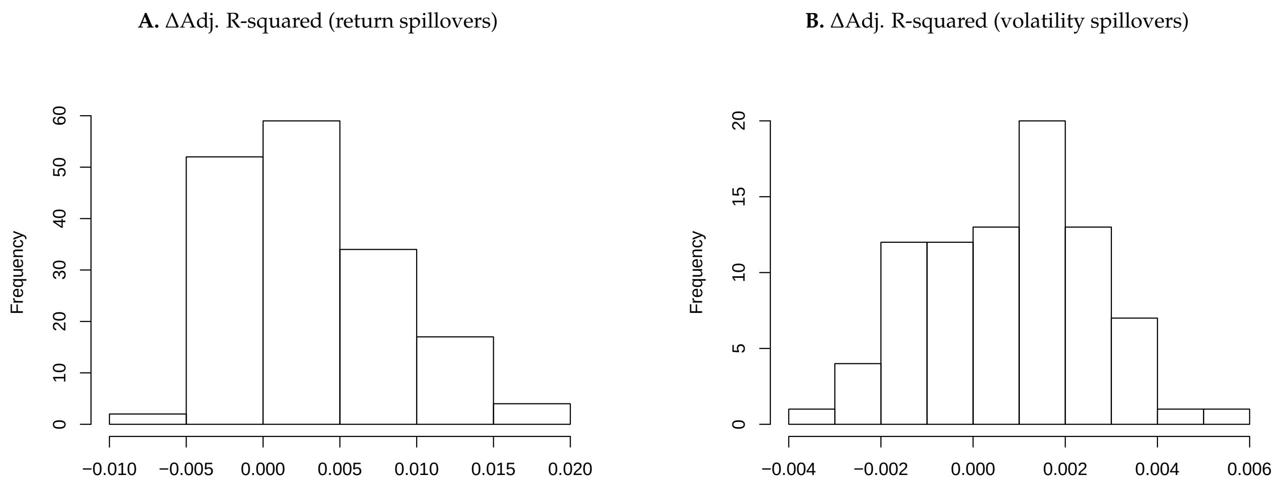


Figure 11. Multi-asset portfolios. This figure shows the marginal contribution of spillover estimates to the key ingredients for portfolio construction using simulated 20-asset portfolios. The graphs illustrate that the marginal contribution is negligible.

3. Empirical Analysis

The simulation study presented in the previous section has shown that return and volatility spillovers affect asset allocation and portfolio optimization, but their effects are all embedded and thus channeled through other assets' characteristics that are widely known as the fundamental ingredients to build a "Markowitz-efficient" portfolio, i.e., expected return, variance, and correlation estimates. In this section, we use the 30 constituents of the Dow Jones Industrial Average (DJIA) stock price index to analyze if the findings derived from the simulation study also hold empirically. Daily closing prices of each stock are retrieved from Thomson Reuters Datastream for the 20-year period from 30 January 1998 to 30 January 2018. Daily returns are calculated as percentage changes of daily closing prices and weekly returns are calculated as percentage changes of Wednesday closing prices.[13]

Expected returns and volatility are respectively estimated as the average and the standard deviation of historical returns.

3.1. Influence of Spillovers on Assets' Characteristics

We empirically examine the links between daily spillovers and daily or weekly assets' characteristics in a regression setting using DJIA constituent stock returns. We prepare the data for the regression as follow. From the 30 constituent stocks, we form $30 \times 29/2 = 435$ unique pairs, each pair then forms a two-asset portfolio. For each portfolio, we estimate the daily conditional variance of its constituents A and B using a VAR(1)-GARCH(1,1) model.[14] Then, we estimate daily return and volatility spillovers from A to B and from B to A using a VAR(1) model developed by Sims (1980) with four variables: two stock return series and two conditional volatility series. For example, the return spillover from A to B is the coefficient of $r_{A,t-1}$ in the regression with $r_{B,t}$ as the dependent variable, in which $r_{A,t}$ and $r_{B,t}$ are respectively the returns of stock A and B on day t.

As spillovers can be bidirectional between A and B, and we employ characteristics of spillover-receiving assets as dependent variables, each pair generates two observations in the cross-sectional regression analysis. In regressions with daily return spillovers as the independent variable, we include a dummy variable that equals 0 if the return spillover is negative and 1 otherwise to take into consideration the dependence of the links between return spillovers and other assets' characteristics on the sign of return spillovers (Figures 1 and 3). The results presented in Table 5 confirm the observed relationships in the simulations. However, it should be noted that there are also some differences between the empirical results and the simulations. First, as the correlations between the stocks are all positive, we only observe the empirical relationship between daily return spillovers and weekly standard deviations of the spillover-receiving asset under positive correlation conditions, corresponding with the blue line in Figure 3b. The negative coefficients of ret_spill_d and positive coefficients of $ret\_spill_d \times dum\_ret\_spill_d$ in regression (5) and (6) are consistent with the shape of the blue line. Second, there is a strong positive relationship between volatility spillovers and expected returns and correlations at both daily and weekly levels (regressions (7)–(10)). The reason is that a volatility spillover positively affects an asset's variance which in turn affects expected returns through a volatility feedback effect. In the simulations, variances and expected returns were assumed to be independent to clearly identify *direct* links from spillovers to each variable. When the volatility feedback is incorporated into the GARCH simulation, however, we observe consistent results for the simulated and the empirical asset returns.

Third, return spillovers are not linked to expected returns in the empirical results (regressions (1) and (2)), while they are strongly positively correlated in the simulations. We propose an explanation for the inconsistency as follows. The observed returns of an asset can be decomposed into two parts: the assets' "own" returns and spillovered returns from other assets, i.e., observed returns (a) = "own" returns (b) + return spillovers (c). While (b) and (c) are possibly correlated, e.g., the asset with greater "own" returns is more likely to be affected by market conditions and therefore more likely to get higher spillovers from other assets, the regression of (a) on (c) cannot control for (b) because it is not observable, i.e., there is no "clean" return free of external influences and spillovers. Thus, the empirical regression setting might be suffering from the omitted-variable bias. Nevertheless, such differences do not affect our overall conclusion based on the simulations and the empirical analysis that there are links from spillovers to other asset characteristics, and that these characteristics are more important for asset allocation.

Table 5. Empirical analysis: Links between spillovers and assets' characteristics. This table presents results of the regressions of various assets' characteristics at daily and weekly frequencies on daily return spillovers (Panel A) and volatility spillovers (Panel B). Within each of 435 pairs of two stocks formed by 30 DJIA constituents, we estimate contemporaneous correlation between the two stocks, return and volatility spillovers from one stock to the other, as well as the expected returns and variances of the spillover-receiving stock. Within each pair, a stock plays either role, spillover giver or spillover receiver. We denote X as the spillover-giving stock and Z as the spillover-receiving stock. $dum\_ret\_spill_d$ is a dummy variably which equals 0 if return spillover is negative and 1 otherwise. Standard errors are in parentheses. *, **, and *** denotes significance levels of 1%, 5%, and 10%, respectively.

	Dependent Variable:					
	$er_{Z,d}$	$er_{Z,wk}$	cor_d	cor_{wk}	$sd_{Z,d}$	$sd_{Z,wk}$
Panel A: Return Spillovers						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ret\_spill_{d,X \to Z}$	−0.001 *	−0.003	−0.102	0.460 **	−0.030 ***	−0.061 ***
	(0.0005)	(0.002)	(0.158)	(0.185)	(0.007)	(0.015)
$dum\_ret\_spill_d$	0.0001 ***	0.0004 ***	0.028 ***	0.035 ***	0.002 ***	0.005 ***
	(0.00003)	(0.0002)	(0.010)	(0.012)	(0.0005)	(0.001)
$ret\_spill_{d,X \to Z} \times$	−0.001	−0.005	0.475 *	0.138	0.088 ***	0.168 ***
$dum\_ret\_spill_d$	(0.001)	(0.004)	(0.287)	(0.337)	(0.013)	(0.027)
Constant	0.001 ***	0.003 ***	0.337 ***	0.302 ***	0.017 ***	0.036 ***
	(0.00002)	(0.0001)	(0.006)	(0.007)	(0.0003)	(0.001)
Adjusted R^2	0.006	0.006	0.029	0.080	0.130	0.110
Panel B: Volatility Spillovers						
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
$vola\_spill_{d,X \to Z}$	0.003 ***	0.011 ***	0.546 **	0.509 *	0.121 ***	0.265 ***
	(0.001)	(0.004)	(0.245)	(0.295)	(0.011)	(0.023)
Constant	0.001 ***	0.003 ***	0.337 ***	0.293 ***	0.017 ***	0.033 ***
	(0.00002)	(0.0001)	(0.006)	(0.007)	(0.0003)	(0.001)
Adjusted R^2	0.012	0.010	0.005	0.002	0.130	0.133

3.2. Influence of Spillovers on Portfolio Characteristics

We now empirically analyze the role of spillovers on the portfolio targeting either minimum variance or maximum Sharpe ratio. We estimate return spillovers and volatility spillovers for each asset in each portfolio in the same way as described in Section 3.1 and calculate the standard deviations of the minimum variance portfolios, the maximum Sharpe ratios, and the weights of the spillover-receiving asset in each two-stock portfolio. Then we examine how much of the variation in portfolio characteristics is explained by spillovers and how much by the traditional or typical ingredients (expected returns, correlations and variances) using the following regression:

$$\begin{aligned} Portf\_char_{A,B} = \alpha &+ \beta_1 ret\_spill_{A \to B} + \beta_2 ret\_spill_{B \to A} \\ &+ \gamma_1 vol\_spill_{A \to B} + \gamma_2 vol\_spill_{B \to A} + \delta Control_{A,B} + \varepsilon \end{aligned} \tag{9}$$

where $ret\_spill_{A \to B}$ and $vol\_spill_{A \to B}$ are, respectively, the estimated daily return spillover and volatility spillover from A to B. $Control_{A,B}$ consists of control variables including the standard deviations, expected returns of A and B and their correlation. $Portf\_char_{A,B}$ represents the dependent variable, which is either the minimum variance, the maximum Sharpe ratio or the corresponding weight of the spillover-receiving asset in the portfolio formed by stocks A and B. Portfolios are also formed based on either daily or weekly returns.

The results are presented in Table 6. Although some coefficients of return and volatility spillovers are statistically significant (mostly in regressions with "weight of asset" as the dependent variable), their economic significance is marginal due to their very small magnitudes. Besides, in both daily-based and weekly-based portfolios, the adjusted R^2 of all regressions only increases marginally (generally less than one percentage point) even after including all spillover measures. Thus, consistent with the simulation study, the empirical results imply that compared to traditional factors including expected returns, variances and contemporaneous correlations, the contribution of spillovers on asset allocation and portfolio optimization is insignificant.

Table 6. Empirical analysis—Effects of spillovers on optimal portfolios. This table presents regression results of model (9) and its nested model without spillovers as independent variables. For each two-asset (A and B) portfolio formed from 30 DJIA constituents, we estimate return spillover ($ret\_spill_{A \to B}$ and $ret\_spill_{B \to A}$), and volatility spillover ($vol\_spill_{A \to B}$ and $vol\_spill_{B \to A}$) from one to the other. Then, we calculate minimum variance and maximum Sharpe ratio of the portfolio, along with their corresponding weights of asset A as dependent variables. Control variables include correlation ($cor_{A,B}$), standard deviations (sd_A and sd_B) and expected returns (er_A and er_B) either at daily frequency (Panel A) or weekly frequency (Panel B). The last row of each Panel presents the difference in adjusted R^2 of the full model and the restricted model without spillovers. t-statistics are in parentheses. *, **, *** denote significance level at 10%, 5%, and 1%, respectively.

Panel A: Portfolios Formed by Daily Returns								
	Minimum Variance Portfolio				Maximum Sharpe Ratio Portfolio			
	Standard Deviation		Weight of Stock A		Sharpe Ratio		Weight of Stock A	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ret\_spill_{d,A \to B}$		−0.00001		0.241 ***		−0.002		−0.072
		(0.001)		(0.076)		(0.005)		(0.143)
$ret\_spill_{d,B \to A}$		−0.006 ***		−0.162		0.014 **		0.115
		(0.002)		(0.099)		(0.007)		(0.186)
$vol\_spill_{d,A \to B}$		−0.009 **		1.113 ***		0.061 ***		1.157 **
		(0.005)		(0.294)		(0.021)		(0.552)
$vol\_spill_{d,B \to A}$		−0.024 ***		−1.671 ***		0.083 ***		−0.841 *
		(0.004)		(0.270)		(0.019)		(0.507)
$cor_{d,A,B}$	0.009 ***	0.009 ***	0.225 ***	0.201 ***	−0.017 ***	−0.018 ***	−0.071	−0.078
	(0.001)	(0.0005)	(0.033)	(0.032)	(0.002)	(0.002)	(0.058)	(0.060)
$sd_{d,A}$	11.136 ***	11.693 ***	−798.858 ***	−709.528 ***	−11.858 ***	−12.376 ***	−775.234 ***	−712.042 ***
	(0.326)	(0.376)	(21.329)	(24.371)	(1.459)	(1.726)	(37.407)	(45.742)
$sd_{d,B}$	7.302 ***	6.425 ***	808.852 ***	694.633 ***	−12.054 ***	−9.700 ***	762.038 ***	702.968 ***
	(0.269)	(0.332)	(17.565)	(21.500)	(1.201)	(1.523)	(30.805)	(40.353)
$er_{d,A}$	0.349 *	0.459 **	−102.477 ***	−95.033 ***	32.120 ***	31.667 ***	790.944 ***	794.214 ***
	(0.198)	(0.187)	(12.931)	(12.139)	(0.884)	(0.860)	(22.679)	(22.784)
$er_{d,B}$	0.537 ***	0.668 ***	5.732	25.201 **	25.679 ***	25.362 ***	−600.309 ***	−593.656 ***
	(0.160)	(0.154)	(10.446)	(10.006)	(0.714)	(0.709)	(18.321)	(18.781)
Constant	0.005 ***	0.005 ***	0.470 ***	0.488 ***	0.016 ***	0.014 ***	0.412 ***	0.405 ***
	(0.0003)	(0.0003)	(0.017)	(0.020)	(0.001)	(0.001)	(0.029)	(0.037)
Adjusted R^2	0.850	0.868	0.911	0.923	0.864	0.874	0.858	0.860
Δ Adjusted R^2	0.018		0.012		0.010		0.002	

Table 6. *Cont.*

Panel B: Portfolios Formed by Weekly Returns								
	Minimum Variance Portfolio				**Maximum Sharpe Ratio Portfolio**			
	Standard Deviation		**Weight of Stock A**		**Sharpe Ratio**		**Weight of Stock A**	
	(9)	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
$ret\_spill_{d,A\rightarrow B}$		−0.004		0.149 *		0.002		−0.067
		(0.003)		(0.078)		(0.016)		(0.148)
$ret\_spill_{d,B\rightarrow A}$		−0.016 ***		−0.169 *		0.044 **		0.242
		(0.003)		(0.099)		(0.020)		(0.188)
$vol\_spill_{d,A\rightarrow B}$		−0.012		1.324 ***		0.118 **		0.600
		(0.010)		(0.288)		(0.058)		(0.547)
$vol\_spill_{d,B\rightarrow A}$		−0.042 ***		−1.894 ***		0.237 ***		−0.698
		(0.009)		(0.263)		(0.053)		(0.499)
$cor_{wk,A,B}$	0.017 ***	0.018 ***	0.223 ***	0.210 ***	−0.030 ***	−0.034 ***	−0.029	−0.038
	(0.001)	(0.001)	(0.026)	(0.027)	(0.005)	(0.005)	(0.046)	(0.051)
$sd_{wk,A}$	5.644 ***	5.932 ***	−194.906 ***	−170.304 ***	−7.572 ***	−8.302 ***	−204.440 ***	−196.203 ***
	(0.158)	(0.185)	(4.815)	(5.463)	(0.920)	(1.100)	(8.389)	(10.374)
$sd_{wk,B}$	3.517 ***	3.165 ***	185.324 ***	155.314 ***	−6.877 ***	−5.067 ***	190.582 ***	180.784 ***
	(0.132)	(0.168)	(4.007)	(4.972)	(0.766)	(1.001)	(6.982)	(9.443)
$er_{wk,A}$	0.102	0.129	−14.100 ***	−12.829 ***	16.388 ***	16.158 ***	156.995 ***	157.661 ***
	(0.085)	(0.081)	(2.574)	(2.380)	(0.492)	(0.479)	(4.485)	(4.519)
$er_{wk,B}$	0.144 **	0.218 ***	−5.416 **	−0.056	12.494 ***	12.174 ***	−120.431 ***	−119.494 ***
	(0.069)	(0.069)	(2.113)	(2.024)	(0.404)	(0.408)	(3.681)	(3.843)
Constant	0.010 ***	0.010 ***	0.497 ***	0.507 ***	0.034 ***	0.028 ***	0.414 ***	0.423 ***
	(0.0004)	(0.001)	(0.014)	(0.018)	(0.003)	(0.004)	(0.024)	(0.034)
Adjusted R^2	0.865	0.880	0.912	0.926	0.838	0.849	0.866	0.867
Δ Adjusted R^2	0.015		0.004		0.011		0.001	

4. Conclusions

This paper is motivated by the large and growing literature on spillovers and the absence of studies that evaluate the importance of spillovers for portfolio management and asset allocation.

We illustrate the relationship between spillovers and returns, variances, and contemporaneous correlations, and show that spillovers are embedded in returns, variances, and correlations and thus included in the key ingredients for asset allocation. For example, a return spillover from X to Z is included in the expected return of Z, the variance of Z and in the correlations between X and Z. Therefore, estimation and identification of such a spillover is redundant for asset allocation. Our analysis is based on spillovers that have the same frequency (e.g., daily) as the return, variance and correlation estimates. While such a setting is typical in the spillover literature, it may be interesting to examine how higher-frequency spillovers affect lower-frequency estimates of correlations, returns and volatility.

Consequently, claims that spillovers have strong implications for asset allocation and portfolio management are misleading in the sense that identification and quantification of spillovers are not necessary. Spillover estimates may help portfolio managers and policy makers to better understand the causes of low or high returns, variances and correlations but it is not clear how, if at all, spillover estimates can enhance portfolios.

We further demonstrate through simulations and empirically using US stock prices that spillovers are generally small in absolute terms and economically insignificant when compared with contemporaneous correlations. In fact, spillovers are often spurious in the sense that they appear to be important as long as other factors are omitted but shrink substantially if such factors are included in the analysis.

Although our empirical analyses focus on the U.S. stock market which is more liquid than other less developed markets, we argue that our conclusions apply to both liquid and illiquid markets alike. Illiquidity leads to a slower incorporation of information into prices and lower price efficiency (Barclay and Hendershott 2008) potentially resulting in larger spillovers. However, as we demonstrated that spillovers are fully embedded in returns, volatility, and correlations of assets, illiquidity does not affect our conclusions.

Future research could try to answer the question why there is an abundance of empirical spillover studies that quantify the connectedness of markets and assets through spillovers without an explicit application to portfolio management and asset allocation.

Author Contributions: Conceptualization, L.T.H. and D.G.B.; methodology, L.T.H. and D.G.B.; formal analysis, L.T.H.; investigation, L.T.H. and D.G.B.; data curation, L.T.H.; writing—original draft preparation, L.T.H. and D.G.B.; writing—review and editing, L.T.H. and D.G.B.; visualization, L.T.H. and D.G.B.; supervision, D.G.B. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1 Google Scholar yields about 10,000 articles based on the search term "volatility spillover" and about 1000 articles based on the search term "return spillover" (as of July 2019).

2 We define spillovers as non-contemporaneous correlations of two markets, assets or asset classes, and we define interdependence or connectedness as contemporaneous correlations of two markets, assets or asset classes. Consistent with the literature we view the terms "return spillover" and "mean spillover" as similar and interchangeable and we also view the terms "volatility spillover" and "variance spillover" as similar and interchangeable.

3 Since our focus is on the marginal effect of spillovers on asset allocation we need to control for other factors and thus do not consider the out-of-sample performance of the generated portfolios.

4 A more general formulation including the same and all higher frequency spillovers is $PI(f) = \sum_{i=1}^{I} \sum_{j=0}^{J} s_i(f+j) + c$ where j denotes the frequency level and J is the highest frequency level, e.g., 1-second returns. The equation represents the idea that spillovers at frequencies f and higher, e.g., daily, hourly, minutes, seconds, are fully embedded in return, variance and correlation estimates at frequency f.

5 Hereafter, by "optimal portfolio", we mean portfolios constructed using Modern Portfolio Theory.

6 The chosen intervals of *er* and *sd* are based on observed empirical distributions of daily stock returns of 30 Dow Jones Industrial Average (DJIA) constituents from 1998 to 2018.

7 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html (accessed on 30 May 2020).

8 We conduct the tests with several different sets of GARCH parameters and find that all the results are qualitatively similar.

9 Analogous to the return spillovers case, the expected returns are randomly generated between 0.03 and 0.08.

10 The contemporaneous correlation parameter a is randomly withdrawn from $[-0.5, 0.5]$ in both return and volatility spillovers. Other parameters are similar to Sections 2.1 and 2.2.

11 When we allow average a to be positive (negative), we find a similar pattern with the blue (red) line in Figure 1c.

12 We also simulate smaller and larger sets of assets and obtain similar results.

13 Due to the well known day-of-the-week effect in which returns are significantly different after the weekend (on Mondays) and before the weekend (on Fridays) (French 1980; Lakonishok and Levi 1982), the middle-of-the-week prices on Wednesday potentially have the least bias compared with other weekdays.

14 We use the VAR(1) model in the mean equation to eliminate return spillovers from volatility spillovers.

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