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Diversification with globally integrated US stocks ☆

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ABSTRACT

We measure market integration at a firm-level for the US stock market with the rest of the world. The properties of firm-level integration are explored across time and industries and then stocks are sorted into high- and low-integration portfolios. The role of the least globally integrated US stocks in domestic and international portfolio diversification is assessed. We show that these stocks can statistically and economically augment diversification potential, especially after 2000. The same stocks can be combined with the US market index to create a portfolio that performs at least as well as an international index portfolio in terms of risk-adjusted returns and tail risk.

1. Introduction

Equity market integration is a pervasive issue in asset pricing and risk management. For investors who are considered rational risk and return optimizers, correlation between markets is of utmost importance. Global diversification and optimal portfolio choice are terms interlinked and heavily influenced by the dependence structure of global markets. If markets are found to be increasingly correlated or integrated then benefits from diversification are diminished and the construction of the optimal portfolio is altered. Thus measuring and managing equity integration is a key issue for global investment strategies.

The literature on market integration is vast with many related papers concentrating on an important question: How has integration between markets evolved through time? The answer is generally found by studying national equity index returns which stands as the foundation of many of the main contributions to the literature. A variety of methods have been employed to measure the time evolution of integration that range from simple correlations (Longin and Solnik, 1995; Goetzmann et al., 2005; Quinn and Voth, 2008; Obstfeld and Taylor, 2003; Rangvid et al., 2016) and conditional correlation models (Christoffersen et al., 2014) to copulas that are fitted to returns of market indices and international asset pricing models (Bartram and Wang, 2015).

In the search for an appropriate measure of integration, Pukthuanthong and Roll (2009) demonstrate that correlation-based methods can be misleading and argue that an integrated stock market should have asset returns which are sensitive to common global equity shocks while Bekaert et al. (2011) construct a measure of market segmentation using differences in industry earnings yields across countries. Billio et al. (2017) use all the previously proposed measures of integration applied to national market indices and compare their resulting patterns through time. They find that no matter the method, the consensus is that global integration is trending upwards, at least since the second half of the 20th century.

All the above papers study global market integration from a national index perspective. To our knowledge, very few papers (Brooks and Negro, 2006; Di Giovanni et al., 2018; Eun et al., 2017 being notable exceptions) study integration on a firm level and those that do, use mostly correlation based measures. For example, Brooks and Negro (2006) use the beta of the global market

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factor as a proxy of the integration of a firm with the world. On the other hand Di Giovanni et al. (2018) use the correlation between the total value-added (total value-added is the difference between revenue and cost of goods sold) growth of a French firm with GDP growth of a foreign country. However, Eun et al. (2017) take a different approach and calculate the integration R-square measure of Pukthuanthong and Roll (2009) for each firm and year. The R-square captures the proportion of stock returns that can be explained by a set of global factors in a time period. We also adopt the Pukthuanthong and Roll (2009) methodology in order to capture the integration patterns of all US domiciled and publicly traded stocks with foreign market factors. In doing so, we expand the degree of granularity by which integration is measured, since we are not focusing on country level market indices but on the individual firms traded in the market in the spirit of Eun et al. (2017).

We then use our firm-level integration measure to examine diversification potential. Diversification as a method of portfolio risk mitigation has been extensively studied by the literature (Levy and Sarnat, 1970; Solnik, 1974; Statman, 1987) with heavy emphasis on geographical equity diversification. However, risk reduction can be achieved by diversification across industries (Heston and Rouwenhorst, 1994) and asset classes such as bonds (Liu, 2016), real estate (Candelon et al., 2021) and precious metals (Vigne et al., 2017) among others.[1] The consensus is that investment in international assets yields better risk reduction results than a purely domestic strategy. However, international diversification benefits have deteriorated due to the increased globalization of world markets (Goetzmann et al., 2005; Pukthuanthong and Roll, 2009; Baele and Inghelbrecht, 2009; You and Daigler, 2010; Christoffersen et al., 2012). This is especially true for country- vs industry-based asset allocations (Marcelo et al., 2013; Bessler et al., 2021).

Our study contributes to the home-made diversification literature which offers another avenue to explain the ‘‘home bias’’ puzzle of French and Poterba (1991), Kang et al. (1997) and Coval and Moskowitz (1999). According to French and Poterba (1991), US investors hold a higher proportion of domestic assets in their portfolio than a mean–variance framework would suggest after taking into account the correlation structure of the US with foreign assets. We add to the work of Errunza et al. (1999), Berrill and Kearney (2010), Cai and Warnock (2012) and Bae et al. (2019) who examine the ‘‘home bias’’ puzzle with the common theme of their work being that investors can trade only US assets and still achieve the level of diversification of an international strategy. Specifically, we show that the portfolio of US stocks that are least driven by foreign market factors can be combined with the S&P500 index to yield diversification benefits indistinguishable from a strategy that invests in the market indices of the 10 most developed countries.

Errunza et al. (1999) propose a method for constructing foreign index mimicking portfolios using only assets that are either domiciled or traded in the US. Their idea is simple; if one can mimic foreign market indices with domestic assets, then one can achieve international diversification without the need to trade abroad. This concept of home-made diversification has also been explored by Bae et al. (2019) who construct portfolios that are exposed to a specific country using imports and exports as a proxy for the real exposure of firms to that particular country. Eun et al. (2017) construct ‘‘local’’ portfolios, based on the R-square measure of Pukthuanthong and Roll (2009) of a stock with global factors within a country, industry or investment style, and assess how these ‘‘local’’ portfolios enhance the diversification potential of international index strategies.

We measure the integration between each publicly traded and domiciled US firm with foreign markets at the firm level annually using the R-square methodology of Pukthuanthong and Roll (2009) for the period 1974–2020. We calculate the R-square from factors constructed from foreign markets only, thus excluding the US market. This specification allows us to study the degree to which foreign shocks affect local US firms and this is our second contribution to the integration literature. In other words, our R-square measure estimates the comovement between a local stock and foreign markets and captures how foreign shocks propagate to the US irrespective of the state of the local market.[2] In general, local investors possess an informational advantage (Coval and Moskowitz, 2001) on their respective country markets, and as such, they are better informed about the integration of the local stocks with the market. However, we show that there is additional value in learning how foreign shocks originating outside of their domestic market propagate to the local equities.

In the second part of our analysis we study the role of the firm-level global integration measure in diversification strategies. Specifically, we construct integration portfolios and focus our attention on the low-integration portfolio and its ability to enhance domestic and international diversification. The diversification benefits of the least integrated stocks are assessed in terms of Sharpe ratio as well as total and tail risk for the full period 1974–2020 and for the old and new millennium sub-periods. Tail risk is an important concept for investors who are averse to extreme losses and, as such, it is beneficial to show whether or not the low-integration portfolio offers lower tail risk.

The main results of our paper can be summarized as follows. First, we find evidence of a positive upward trend for the integration of the US market and its industries at the firm-level with spikes in periods when the markets are distressed. Even though the trend is positive for all industries, some industries such as Steel, Coal, Chemicals or Automobiles experience a higher rate of integration while others such as Games, Food or Healthcare are becoming integrated at a slower pace.[3] There is also a large difference in the integration level between the period before and after 2000 and between the most and least integrated industries. Furthermore, stocks that belong to the bottom decile in terms of their R-square exhibit a constant low level of integration while the integration of the top decile is more volatile and similar to the pattern of the whole US market.

Second, the low-integration portfolio is not spanned by the set of US and foreign indices of developed countries meaning that it may offer diversification opportunities beyond those of the indices. We show that it can be optimally combined with the S&P 500

[1] A thorough bibliometric review on diversification is given by Migliavacca et al. (2023).

[2] Qin et al. (2022) propose an adjustment of the R-square measure during crisis periods to account for factor heteroscedasticity.

[3] Donadelli and Paradiso (2014) also report industry heterogeneity when measuring financial integration in Emerging markets.

or with both the S&P 500 and the foreign indices under the mean–variance framework generating higher risk-adjusted returns and lower tail risk than the indices alone. Furthermore, the combination of S&P 500 with the low-integration portfolio can bring the tail risk, as measured by the 95% Value-at-Risk and the Sharpe ratio, to the same level as an international index strategy. Third, we find that portfolios comprised solely of the least globally integrated US stocks offer additional domestic diversification benefits in both total and tail risk reduction compared to portfolios of high integrated stocks. This is a consequence of low (high) integrated US stocks being less (more) correlated with each other.

Third, the diversification benefits of the low integrated stocks are stronger after the year 2000. This is in line with the increasing integration pattern being most prominent in the new millennium when the ability of the "Low" portfolio to be less correlated with both the US and the world is needed the most. This effect is reflected both in economically and statistically significant Sharpe ratio gains and declines in tail risk after 2000. For example, when we augment the S&P 500 and the international index strategy with the low-integration portfolio, we observe a Sharpe ratio increase of 150% after 2000 versus 33% before 2000 and an increase of 32% versus 14% for the two strategies respectively when short sales are not allowed. For the same strategies, low integrated stocks reduce tail risk by 15% after 2000 versus 3% before 2000 in the former case and 18% versus 12% in the latter. These findings highlight the importance of the low-integration portfolio in global diversification strategies in recent years when diversification benefits among the developed market countries have been significantly reduced. Our results are robust against a battery of robustness checks.

The remainder of this paper proceeds as follows. Section 2 gives the details of our data and methodology. Section 3 presents our empirical findings. We discuss several robustness checks in Section 4 and Section 5 concludes.

2. Data & methodology

2.1. Data

The analysis below employs data from two separate sources; CRSP and Datastream. Our sample consists of all common stocks (Center for Research in Security Prices (CRSP) share codes 10 and 11) from the daily and monthly CRSP tape trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) between January 1973 and December 2020.

Second, we gather daily equity index series that span from 1973 to 2020 for a set of 10 major developed countries from Thomson Reuters Datastream as found in Pukthuanthong and Roll (2009). These countries are Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Singapore, Switzerland, and the UK. We prefer to work with total return indices, if available, over price indices as the former include dividend payments. Table 1 provides details on the indices. All foreign-denominated indices are converted to US dollars. This conversion represents a common practice in empirical studies of international financial markets (see for example Pukthuanthong and Roll, 2009). Even though, this practice eliminates exchange rate noise, it does not eliminate exchange rate risk. Lee et al. (2023) raise a potential issue on the positive relationship between foreign exchange rate risk and equity "home bias" but empirical evidence (Van Wincoop and Warnock, 2010) is contradictory. Thus we argue that the conversion to a common currency does not have a substantiative impact upon our results.

We choose to work with returns at a weekly frequency for the estimation of the firm-level integration measure. This decision is guided by the need to strike a balance between conflicting objectives. First, we require a satisfactory number of returns in each period to calculate PCA-based integration estimates. This suggests the need for reasonably high-frequency returns. Second, we wish to minimize the influence of microstructure issues commonly observed in higher-frequency returns and infrequent trading of individual stocks.

We treat daily returns $|r| \geq 10$ or (1000%) as missing in order to minimize the effect of outliers in our analysis. Weekly returns are aggregated from daily returns from Thursday to Thursday as $r_{weekly} = \Pi_{j=1}^{5}(1 + r_{daily,j}) - 1$. When a return value for any trading day between Thursday and Thursday is missing, then the weekly return is considered missing.

2.2. Measuring firm-level integration

We employ the methodology of Pukthuanthong and Roll (2009) for measuring the integration of US domiciled and publicly traded firms with global market factors in annual intervals.

CRSP weekly returns of a time period are regressed against the first M Principal Components (PCs) constructed by the Principal Component Vectors (PCVs) of the market return matrix of the previous period. The return matrix includes the international market indices[4] except the US. In that framework, the M Principal Components as estimated from only international markets are treated as global factors that proxy the world economic environment.

$$\vec{r}_{i,t} = c\vec{1} + F_t\vec{b}_{i,t} + \vec{e}_{i,t}, \tag{2.1}$$

where $\vec{r}_{i,t} \in \mathfrak{R}^{N_{i,t}\times 1}$ is a column vector of the returns of stock i at period t, c is the constant term, $\vec{1}$ is a $\mathfrak{R}^{N_{i,t}\times 1}$ vector of ones, $F_t \in \mathfrak{R}^{N\times M}$ is the return matrix of the M Principal Components and $\vec{e}_{i,t}$ is the error term. $N_{i,t}$ is the number of stock returns

[4] In the original paper of Pukthuanthong and Roll (2009), the daily return matrix of eastern countries is augmented by the lagged returns of western markets. In our case, lagged returns are not included in the return matrix X_t for two reasons; first, we use weekly returns thus there is no information leak from one market to another due to time-zone differences and secondly, the US market is the last trading market in a given day or week.

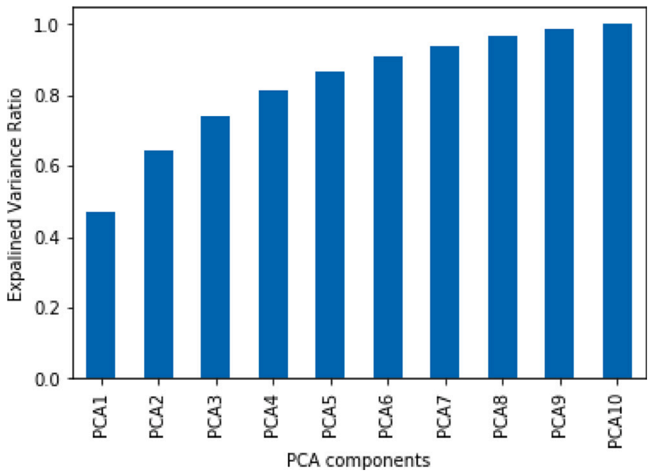


Fig. 1. Cumulative Explained Variance Ratio of the 10 PCA components.
Notes: The figure plots the cumulative explained variance ratio of the ten Principal Components as extracted from the largest by market cap indices in the weekly return regime. The indices are from Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Singapore, Switzerland and UK. It is clear that on average the first five Principal Components can explain almost 85% of the total variance of the return matrix. We use the 85% bound as our decision making criterion.

used in the regression and it varies across stocks i and time t. The matrix F_t is calculated as $F_t = X_t \tilde{P}_{t-1}$ where $\tilde{P}_{t-1} \in \Re^{K\times M}$ is the PCA matrix of the covariance matrix of the Market Index returns X_{t-1} of the previous period or the eigenvector matrix of $\left(X_{t-1} - \bar{X}_{t-1}\right)^T \left(X_{t-1} - \bar{X}_{t-1}\right)$ where $\bar{X}_{t-1}$ demeans the columns of $X_{t-1} \in \Re^{N_{t-1}\times K}$. The PCs that we construct are out-of-sample since we apply the PCVs of the previous period t-1 to the demeaned return market index matrix of the current period t.

Our measure of firm-level integration is the adjusted R-square of Eq. (2.1) which is estimated for every calendar year. In the weekly return regime, a stock i at time t has a valid adjusted R-square when there are at least 30 valid observations in the current calendar year t.

By definition, the R-square captures the percentage of the variation of a stock's returns in a year that is explained by the variation of the global factors' returns. Intuitively, the R-square in that setting measures how much global factors affect a US stock by incorporating all international markets in a single regression formula with a simple and direct interpretation. The higher the adjusted R-square is for a stock, the more integrated it is with the global economy as proxied by the out-of-sample principal components of the international indices. A value of 1 corresponds to total integration while a value of 0 to total segmentation. Since we use the adjusted R-square to define firm-level integration instead of just the R-square, segmentation can correspond to negative values.

We choose to work with five (M=5) principal components in our integration regressions in (2.1). This choice is guided by the data since five eigenvectors are typically enough to explain on average 85% of the variation in our set of equity index returns. Fig. 1 shows the average explained variance ratio for the 10 largest by market cap country indices (Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Singapore, Switzerland, and UK).

2.3. Overview of mean–variance spanning tests

We provide an overview of the spanning tests that we use to assess the diversification potential of the integration portfolios of Section 3.4.

Following the methodology pioneered by Huberman and Kandel (1987), we run three sets of spanning tests that differ depending on the benchmark assets used. The first set corresponds to the domestic case where the benchmark is the S&P 500. The second set is for the purely foreign case and the benchmark assets are the total market return indices used for the definition of R-square which we will denote as TRMIs from now on. The third set covers the international case for which both the S&P 500 and the 10 TRMIs are employed in the analysis.

$$R_i = \alpha_i + \beta_i^{(SP)} S\&P500 \tag{2.2}$$

$$R_i = \alpha_i + \beta_i^{(C1)} TRMI^{(C1)} + \cdots + \beta_i^{(C10)} TRMI^{(C10)} \tag{2.3}$$

$$R_i = \alpha_i + \beta_i^{(C1)} TRMI^{(C1)} + \cdots + \beta_i^{(C10)} TRMI^{(C10)} + \beta_i^{(C11)} S\&P500 \tag{2.4}$$

where R_i are monthly returns of integration portfolio i and $TRMI^{(Ck)}$ is the total return market index (TRMI) of country k = 1,..,10.

The null hypothesis H_0 of all the spanning tests is $\alpha_i = 0$ and $\delta_i = 1 - \sum_{k=1}^{K} \beta_i^{(Ck)} = 0$ where K is the total number of test assets in Eqs. (2.2)–(2.4). If H_0 is not rejected, then portfolio i can be perfectly replicated by the returns of the benchmark assets and thus it is redundant.

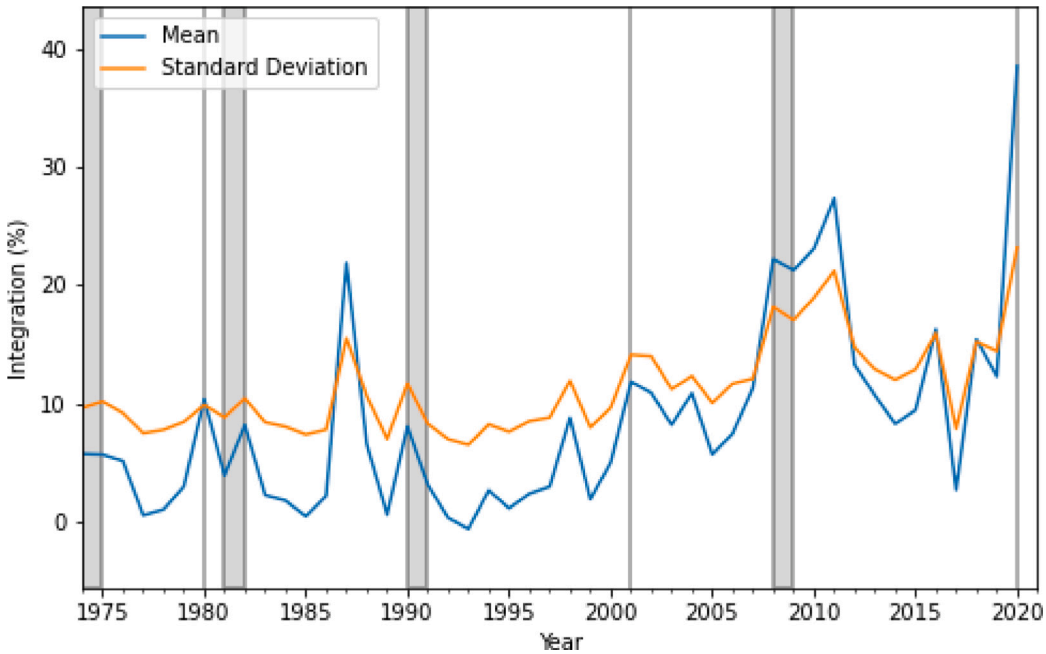


Fig. 2. Global integration level of the US market for the period 1974–2020.
Notes: Figure plots the mean (%) and standard deviation (%) of global integration for all US domiciled and traded stocks. Global integration is measured as the adjusted R-square of a regression of principal components of foreign market country indices against the returns of a stock. The procedure is described in detail in Section 2.2. The integration measure is computed on an annual calendar basis from 1974 to 2020 using weekly returns. The gray shaded areas correspond to US recession periods as defined by NBER.

When there is only one test asset, as is the case with our analysis, the statistic for H_0 is given by:

$$HK = \left(\frac{1}{V} - 1\right)\left(T - \frac{K-1}{2}\right) \tag{2.5}$$

where T is the number of observations used in the estimation of the Eqs. (2.2)–(2.4), K is the number of benchmarks (K=1, 10, 11) and V is the ratio of the determinant of the Maximum Likelihood estimator of the error covariance matrix of the unrestricted model (no spanning) to that of the restricted model (spanning). In other words, the HK statistic is a Likelihood Ratio test which we will denote as LR. Our sample covers January 1975 to December 2020 or T=552 months. Kan and Zhou (2012) proved that under conditional normality of returns, HK in (2.5) follows the F-distribution, $F(2, T-K-1)$.

We also apply the step-down tests[5] as described in Kan and Zhou (2012) for all integration portfolios. Under these tests, the null hypothesis of spanning, $H_0 : \alpha_i = 0$ and $\delta_i = 0$ can be decomposed into two sub-hypotheses; the first tests if the tangency portfolios of the two efficient frontiers are the same, $H_0^{(1)} : \alpha_i = 0$, while the second tests if the global minimum variance portfolios are the same, $H_0^{(2)} : \delta = 0$ given that the tangency portfolios are, $\alpha_i = 0$. If spanning is rejected due to the first sub-hypothesis, then the augmented frontier has a statistically different Sharpe ratio than the one generated by the benchmark assets alone. On the other hand, if spanning is rejected due to the second sub-hypothesis, then the global minimum variance portfolios (GMVPs) of the frontiers are statistically different.

3. Empirical findings

3.1. Integration across stocks

The US integration with the world market is uncovered by aggregating the individual integration measure of all US incorporated and publicly traded stocks in our sample. The integration mean and standard deviation of all US firms are plotted in Fig. 2 which, upon a simple visual inspection, indicates the increasing integration of the US through the years.

Apart from the increasing time trend of integration, three periods of inflated R-square measures are also observed; the first period with a mean R-square of 22% is the year 1987 when the market crashed in October in a black swan event; the second period when the mean R-square is as high as 22% corresponds to the recent global financial crisis of 2007–09; the third period with a mean R-square of 38% is recorded in 2020 when the Covid-19 pandemic markedly affected the world markets. The effect of the mortgage

[5] Raymond Kan kindly provides Matlab code for the routines of all test statistics in his website http://www-2.rotman.utoronto.ca/~kan/research.htm.

Table 1
Equity market indices and summary details.

Country	Index identification	DataStream mnemonic	Provider	Constituents
Australia	Total Market Index	TOTMAU$	Datastream	Majority of Australian stocks
Canada	Total Market Index	TTOCOMP	Standard and Poors (S&P)	250 largest Canadian stocks
France	Total Market Index	TOTMKFR	Datastream	Majority of French stocks
Germany	Dax 30 Index	DAXINDX	Deutsche Boerse	30 largest German stocks
Hong Kong	Hang Seng Index	HNGKNGI	Hang Seng Bank	60 largest Hong Kong stocks
Italy	Total Market Index	TOTMIT$	Datastream	Majority of Italian stocks
Japan	Tokyo Stock Price Index	TOKYOSE	Tokyo Stock Exchange	All Japanese stocks
Singapore	Total Market Index	TOTXTSG	Datastream	Majority of Singaporean stocks
Switzerland	Total Market Index	TOTMKSW	Datastream	Majority of Swiss stocks
UK	Total Market Index	TOTMUK$	Datastream	Majority of UK stocks
US	S&P 500 Composite Index	S&PCOMP	Standard and Poors (S&P)	500 largest US stocks

Notes: The table provides the list of the equity market indices from DataStream, a division of Thomson Reuters. "Index identification" provides the name of the time series and "DataStream mnemonic" refers to the DataStream mnemonic. The columns "Provider" and "Constituents" refer to the source of the index and its content, respectively.

crisis lasts from 2008 to 2011. The dispersion of integration across firms is fairly stable throughout the period 1974–2020 and rises sharply when markets are distressed. Table 2 summarizes the statistical properties of the firm-level integration measure beyond the first and second moment. The distribution of integration is skewed to the right but is not always leptokurtic meaning that there is a continuum of non-normally distributed R-square values that are concentrated more on the right tail.

3.2. Integration across industries

We now study integration across industry portfolios. In each year, we map each firm to an industry using its four-digit SIC code according to the definition that was suggested by Fama–French.[6]

We average the R-square of all firms in an industry for all years except 1987 to construct an industry-specific integration measure and then, we rank each industry based on that. By definition, the industry-specific R-square reveals the consistently most integrated sectors throughout our sample period. For instance, we find that Steel, Fabricated Products and Machinery (FabPr), Coal, Chemicals and Automobiles and Trucks (Autos) are consistently the top five most integrated industries in the period 1974–2020 while Games, Food, Healthcare (Hlth), Beer and Other belong to the bottom five.

The behavior of the integration of industries is formally tested via linear time trends. Table 3 reports the t-statistics of the regression results for the 30 industry portfolios. All industries experienced an increase in integration as demonstrated by the positive and significant linear time trend. The ranking of the magnitude of the trend coincides with the ranking of our industry-specific integration measure. For instance, four of the five most integrated industries, namely Steel, Coal, Fabricated Products and Machinery, and Oil, exhibit the highest upward trend with values of 0.68%, 0.65%, 0.65% and 0.60% per year, respectively. The industry with the fifth highest trend is Aircraft, Ships, and Railroad Equipment (0.59%/year) while Automobiles and Trucks and Chemicals tie in sixth place (0.58%/year). Similar results hold for the bottom five least integrated industries with four of them, Healthcare, Beer, Other and Food being also at the bottom based on the industry-specific integration measure. In general, all industries are becoming more integrated with time but with a different rate as measured by the trend coefficient.

Fig. 4 plots the average integration level of the most and least integrated industries in terms of both the total integration measure and the magnitude of the linear trend coefficient. The difference in integration of the two groups is evident from Figs. 4(a) and 4(b). The Autos, Coil, FabBr, Oil and Steel industries are far more integrated than Games, Food, Healthcare Beer and Other industries. Even though both groups experience a shift in integration in recession periods, the former group is much more sensitive to market distress than the latter.

3.3. Benefits from stock level low integration in the US market

We can use our firm-level integration estimates in order to assess the domestic diversification benefits among the high or low integrated stocks in an experiment in the spirit of Solnik (1974). Specifically, we examine how portfolio risk is reduced as we add more stocks to the portfolio in a simulation exercise for the period 1975–2020. For the simulation, two diversification strategies are considered: diversification across i) high integrated stocks, and (ii) low integrated stocks.

To conduct the experiment, we sort stocks into decile portfolios at the start of each calendar year t, based on their integration measure in the previous year t-1. To form the simulated U.S. N-stock high-integration portfolios, we randomly draw N stocks out of an average of M=446 stocks[7] from the top decile for each year t and equal-weight them. The low-integration portfolios are constructed

[6] The exact details of the Fama–French 30 Industry Classification can be found at their website https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html.

[7] The number of stocks, M, that belong to the top decile integration portfolio ranges over the years. Specifically, the minimum number of high integrated stocks is 339 in year 1978 while the maximum is 675 in 1998 with the average number of stocks being 446 for the period 1975–2020.

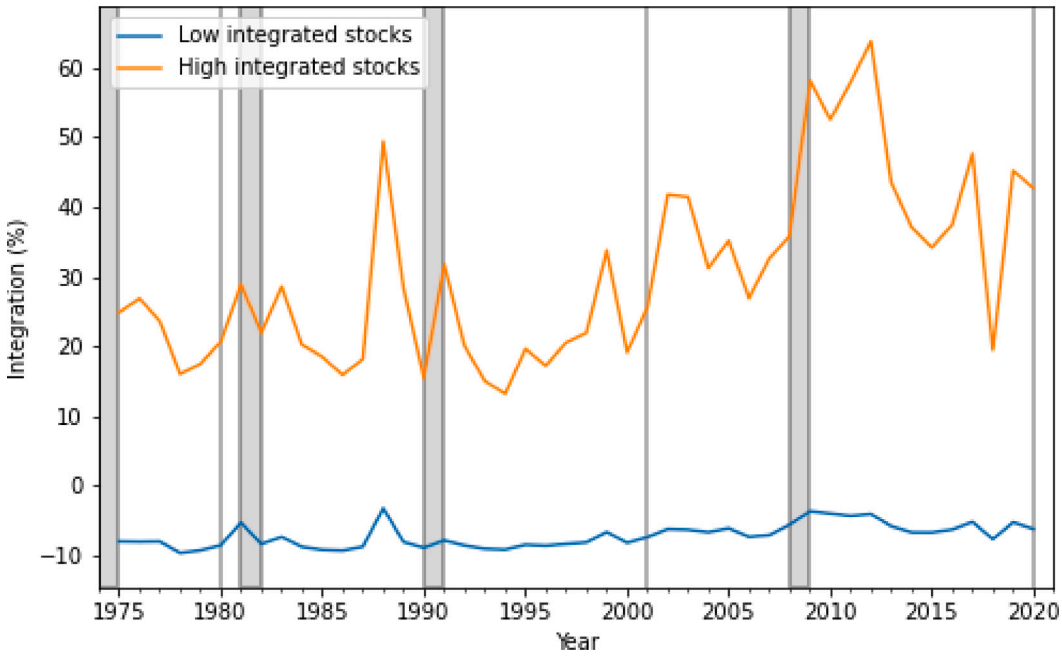
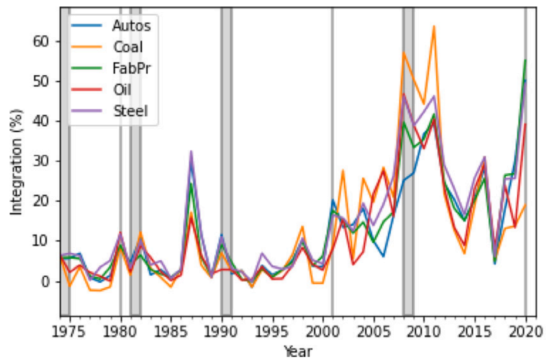
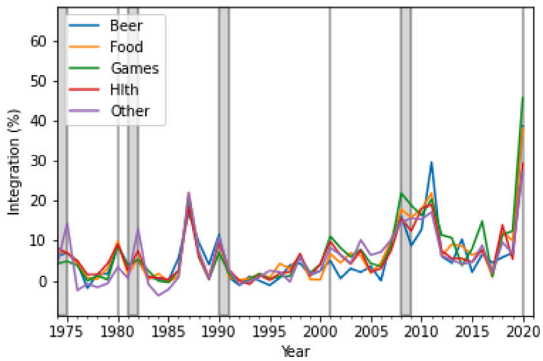


Fig. 3. Ex-ante integration of high and low globally integrated US stocks for the period 1975–2020.
Notes: Figure shows the average ex-ante integration level of high and low globally integrated US stocks for the period 1975–2020. Global integration is measured as the adjusted R-square of a regression of principal components of foreign market country indices against the returns of a stock. The integration measure is computed on an annual calendar basis from 1974 to 2020 using weekly returns. At the start of each calendar year t, we sort stocks into decile portfolios based on their adjusted R-square of the previous year t-1, thus forming 10 integration portfolios for the rest of the year. The "Low" and "High" portfolios consist of the 10% least and most integrated stocks. The gray shaded areas correspond to US recession periods as defined by NBER.



(a) Most integrated industries

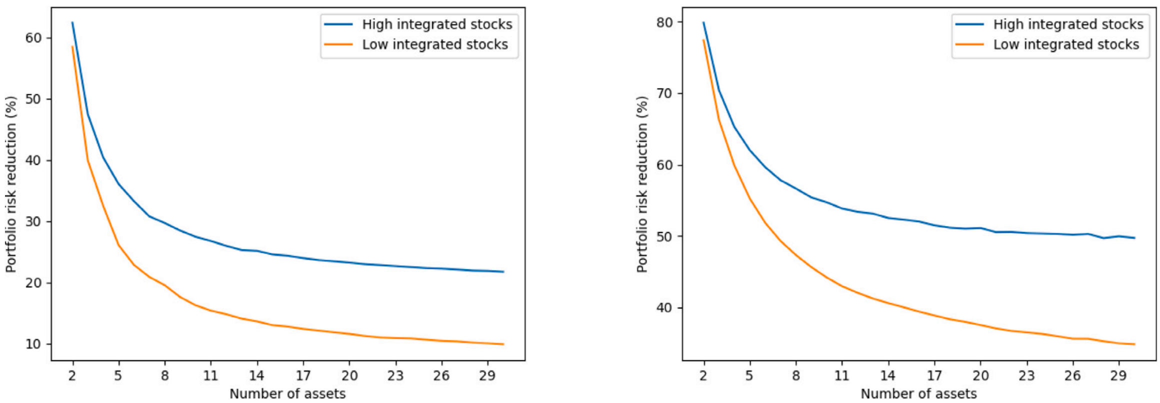


(b) Least integrated industries

Fig. 4. Most and least integrated Fama–French industries for the period 1974–2020.
Notes: Figs. 4(a) and 4(b) show the average integration level of the bottom 5 least and top 5 most integrated Fama–French industries for the period 1974–2020, respectively. The most integrated industries include Steel, Fabricated Products and Machinery (FabPr), Coal, Chemicals and Automobiles and Trucks (Autos) and Oil. The least integrated industries include Games, Food, Healthcare (Hlth), Beer and Other. The Other category consists of firms that could not be assigned to an industry based on the definition of Fama–French. The gray shaded areas correspond to US recession periods as defined by NBER.

in the same manner with the difference that the N stocks are now sampled from the bottom decile. The annual rebalancing of the random N-stock integration portfolios allows us to construct a monthly return time series for the entire period of 1975–2020. The number of stocks in the simulated portfolios ranges from N=1 to 30 and the average portfolio risk measure for each N is calculated from 500 replications. We consider the variance and the 95% Value-at-Risk as our measures of portfolio risk. Fig. 5 examines the relation between portfolio risk and domestic integration-based diversification for the full sample period 1975–2020 using monthly frequency data.

Each curve in Fig. 5(a) plots the portfolio variance, expressed as a percentage of the average variance of individual stocks (N=1), as a function of the number of securities $N \geq 2$ included in the portfolio. The upper and lower curves plot the portfolio variance reduction when investors diversify with high and low globally integrated US stocks, respectively. The variance of the low-integration



(a) Portfolio variance reduction

(b) Portfolio 95% Value-at-Risk reduction

Fig. 5. Portfolio risk reduction for high/low integrated stocks for the period 1975–2020.
Notes: Fig. 5 examines the relation between portfolio risk and domestic integration-based diversification. Each curve in Fig. 5(a) plots the portfolio variance, expressed as a percentage of the average variance of individual stocks, as a function of the number of securities N included in the portfolio. The upper and lower curves plot the portfolio variance reduction when investors diversify with high and low globally integrated US stocks, respectively. To conduct this analysis, we sort stocks into decile portfolios at the start of each calendar year t, based on their integration measure of the previous year t-1. To form U.S. high-integration portfolios, we randomly draw N stocks from an average of 446 stocks from the top decile for each year t and equal-weight them. The number of stocks in the simulated high-integration portfolio ranges from N=1 to 30 and the average portfolio variance for each N is calculated from 500 replications. The low-integration portfolios are constructed in the same exact manner with the difference that stocks are now sampled from the bottom decile. Fig. 5(b) plots the portfolio Value-at-Risk at the 95% level, expressed as a percentage of the average 95% Value-at-Risk of individual stocks, as a function of the number of securities N included in the portfolio. Monthly data from January 1975 to December 2020 have been employed in the analysis.

portfolio is reduced asymptotically to 10% while that of the high-integration only to 22% of that associated with holding an average stock. We clearly see a difference in total risk reduction of 12% between the two strategies. This difference in variance reduction implies that either the average correlation of highly integrated stocks is greater than that of the low integrated stocks or that their variance is higher.

Fig. 5(b) plots the portfolio Value-at-Risk at the 95% level, expressed as a percentage of the average 95% Value-at-Risk of individual stocks (N=1), as a function of the number of securities $N \geq 2$ included in the portfolio. The 95% VaR of the low- and high-integration portfolio is reduced to 35% and 50%, respectively. Again, a difference in tail risk reduction of 15% is documented which is much larger and more meaningful than that of total risk. Thus, low integrated stocks offer not only total risk reduction but also tail risk reduction as is evident from the Value-at-Risk difference of the two portfolios.

We conclude that, even though, the low integration portfolios are formed on the basis of a measure of integration of the US stocks with foreign markets, the stocks belonging to it offer diversification benefits in terms of total and tail portfolio risk reduction for a US domestic investor.

3.4. Integration portfolios

We now describe the formation of the integration portfolios. We will show in later sections that these portfolios along with the S&P500 will be the assets that capture the benefits of home-made diversification. Specifically, we will show that the portfolio of the least globally integrated US stocks can be optimally combined with the local market index yielding the same or better diversification benefits than international market index strategies.

At the start of each calendar year t, we sort stocks into decile portfolios based on their integration measure of the previous year $t-1$, thus forming 10 equal- or value-weighted integration portfolios for the rest of the year. The high-integration portfolio denoted as "High" contains the top 10% most globally integrated US stocks while the low-integration portfolio ("Low") contains the bottom 10% least integrated stocks. The formation of the integration portfolios in year t requires only information that is available at the end of year $t-1$, namely, the firm-level R-square values, and as such they are constructed out-of-sample. We work with monthly frequency return data from January 1975 to December 2020.

Panel A of Table 4 reports the return and risk statistics of the 10 equal-weighted integration portfolios. The low-integration portfolio outperforms the high-integration one in terms of the Sharpe and Sortino ratio. The former yields an annualized Sharpe and Sortino ratio of 0.71 and 1.33 while the latter yields 0.55 and 0.88. The return distribution of the "Low" and "High" portfolio differs based on the empirical quantiles and moments. The most notable differences are found in the left tail of the distribution where the Value-at-Risk at the 95% level of the least integrated stocks is lower than that of the most integrated stocks with reported values of 6.93% and 8.88%, respectively. This finding is reflected in the downside risk-adjusted return as captured by the Sortino ratio. The same results as reported in Panel B of Table 4 hold for the "Low" and "High" portfolio when stocks are value-weighted but the pattern is not strictly monotonic across the R-square deciles. In terms of diversification within these integration portfolios,

Table 2
Summary statistics of US firm-level integration.

Year	Firms	*Mean*	*Std.Dev.*	*Skewness*	*Kurtosis*	*Median*	Min	Max
1974	3541	5.77	9.64	0.62	0.19	4.78	−15.94	48.71
1975	3461	5.70	10.18	0.91	0.94	3.75	−19.27	53.08
1976	3492	5.16	9.21	0.71	0.55	3.83	−16.84	50.59
1977	3419	0.58	7.51	0.94	1.40	−0.61	−17.68	37.25
1978	3479	1.07	7.79	1.10	2.10	−0.34	−18.10	53.85
1979	3464	3.00	8.46	0.95	1.38	1.71	−18.12	43.69
1980	3633	10.39	9.89	0.35	0.04	9.92	−16.85	46.99
1981	3953	3.93	8.85	0.87	1.13	2.64	−18.98	48.74
1982	3962	8.20	10.45	0.51	−0.01	7.17	−17.94	50.90
1983	4252	2.28	8.43	1.02	1.36	0.70	−17.65	51.67
1984	4480	1.82	8.06	0.93	1.30	0.53	−18.24	43.13
1985	4521	0.49	7.40	1.07	1.92	−0.76	−19.07	44.37
1986	4589	2.20	7.81	0.86	1.13	0.98	−18.55	41.96
1987	5058	21.87	15.51	0.17	−0.57	21.32	−13.48	71.66
1988	4874	6.58	10.65	0.74	0.32	4.85	−18.43	56.91
1989	4769	0.63	7.02	0.91	1.04	−0.48	−17.66	37.56
1990	4769	8.08	11.70	0.75	0.32	6.17	−17.66	56.40
1991	4742	3.16	8.31	0.73	0.53	1.90	−17.65	42.98
1992	5309	0.36	7.01	1.01	1.83	−0.73	−19.16	42.40
1993	5714	−0.58	6.53	1.02	1.38	−1.80	−16.17	33.89
1994	6248	2.68	8.25	0.86	0.79	1.26	−17.23	42.56
1995	6318	1.18	7.63	1.10	1.66	−0.38	−17.76	40.52
1996	6686	2.39	8.52	1.21	2.15	0.75	−17.02	52.24
1997	6847	2.99	8.83	1.10	1.49	1.24	−17.12	50.52
1998	6636	8.81	11.92	0.91	0.64	6.70	−14.74	59.99
1999	6128	1.93	8.00	1.14	1.72	0.42	−17.60	47.58
2000	5978	5.01	9.65	1.01	1.12	3.09	−16.21	63.36
2001	5478	11.85	14.12	0.90	0.42	9.05	−13.10	65.27
2002	5061	10.91	14.00	1.13	1.30	7.87	−16.60	75.08
2003	4694	8.21	11.22	0.80	0.35	6.13	−14.53	59.32
2004	4580	10.88	12.33	0.63	−0.10	9.13	−14.47	60.41
2005	4503	5.72	10.06	0.96	0.90	3.95	−15.10	49.71
2006	4469	7.47	11.69	1.15	1.57	5.05	−18.30	62.62
2007	4349	11.34	12.11	0.72	0.26	9.64	−12.77	61.66
2008	4231	22.20	18.16	0.58	−0.10	20.20	−16.16	84.17
2009	3929	21.25	17.06	0.35	−0.63	19.77	−10.66	75.34
2010	3788	23.06	18.91	0.38	−0.68	21.21	−14.37	77.75
2011	3657	27.33	21.20	0.19	−0.97	26.42	−14.15	83.10
2012	3535	13.27	14.73	0.78	−0.02	10.23	−10.18	66.45
2013	3455	10.71	12.90	0.80	0.41	8.83	−16.74	65.75
2014	3556	8.29	12.02	0.99	0.66	5.67	−14.26	60.23
2015	3566	9.46	12.88	1.05	0.90	6.52	−15.40	67.88
2016	3460	16.26	15.93	0.64	−0.30	13.22	−17.92	70.16
2017	3402	2.73	7.88	0.93	0.95	1.36	−14.36	44.37
2018	3426	15.43	15.21	0.60	−0.29	12.88	−14.03	70.30
2019	3427	12.30	14.42	0.88	0.32	8.92	−13.63	68.17
2020	3430	38.49	23.17	−0.11	−0.92	39.53	−22.44	89.31

Notes: The table shows the summary statistics of the integration measure of Pukthuanthong and Roll, 2009 for all US incorporated common share stocks. Integration is defined as the adjusted R-square of the regression in Eq. (2.1) when the number of valid return observations N exceeds 30.

the Portfolio Diversification Index (PDI) of Rudin and Morgan (2006) suggests that the low-integration portfolio is less diversified (PDI value of 2.94) than the high-integration portfolio (PDI of 3.39). However, this pattern is reversed in the equal-weighted case where the low-integration portfolio (PDI of 7.27) is more diversified than the high-integration portfolio (PDI of 6.89). In order to minimize the effect of small-cap and, possibly, illiquid stocks, we work with value-weighted integration portfolios in our subsequent analysis.

In Panel C of Table 4, the average global and domestic integration of stocks when sorted in deciles based on their R-square measure is shown. We also report the domestic integration level defined as the adjusted R-square of a regression of weekly stock returns on the CRSP value-weighted index in a calendar year. The integration pattern along the deciles is strictly monotonic. The values range from −7.3% (a negative value corresponds to a very low R-square of almost zero) for the "Low" portfolio to 29.5% for the "High". The domestic pattern is similar.

In Fig. 3 we report the annual time series of the average ex-ante level of global integration of the low- and high-integration portfolio. The ex-ante value is the value of the R-square that we use at the start of each calendar year t for the formation of integration portfolios. The ex-ante difference of average integration between the two extreme portfolios is large as expected from decile based sorts. Low integrated stocks stay disconnected from world markets even in periods of economic turmoil while, on the

Table 3
Time trend of industry portfolios.

	Autos	Beer	Books	BusEq	Carry	Chems	Clths	Cnstr	Coal	ElcEq
LTrend	0.58***	0.19**	0.28***	0.39***	0.59***	0.58***	0.39***	0.52***	0.65***	0.39***
	(0.11)	(0.09)	(0.08)	(0.09)	(0.13)	(0.10)	(0.11)	(0.11)	(0.14)	(0.09)

	FabPr	Fin	Food	Games	Hlth	Hshld	Meals	Mines	Oil	Other
Ltrend	0.65***	0.31***	0.24***	0.32***	0.17**	0.31***	0.35***	0.46***	0.60***	0.21***
	(0.11)	(0.10)	(0.09)	(0.10)	(0.07)	(0.09)	(0.12)	(0.09)	(0.10)	(0.07)

	Paper	Rtail	Servs	Smoke	Steel	Telcm	Trans	Txtls	Util	Whlsl
Ltrend	0.53***	0.28***	0.33***	0.23**	0.68***	0.32***	0.48***	0.29***	0.40***	0.40***
	(0.10)	(0.09)	(0.08)	(0.10)	(0.11)	(0.08)	(0.10)	(0.08)	(0.13)	(0.10)

Notes: The table shows the linear time trend of the equal-weighted integration time series of industry portfolios as classified by Fama and French. We split the regression results into three Panels of 10 industries each for clarity. LTrend stands for Linear Trend and the values inside the parentheses correspond to the White, 1980 errors of the estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

contrary, high integrated stocks are more sensitive to global events. In other words, we find that even though the US market is becoming more integrated as time elapses, there is always a subset of firms that consistently exhibit a low level of integration and they are immune to foreign shocks. We later argue that these low integrated firms that are minimally affected by global factors constitute a good choice for US investors who wish to gain diversification benefits within developed markets.

3.5. Mean–variance spanning tests: Are low integrated stocks different?

We now formally test if the low-integration portfolio can be spanned by the 10 TRMIs and the S&P 500 Composite index. If the "Low" portfolio is spanned by the TRMIs, then the additional gains from diversification with low integrated stocks will be insignificant. If spanning is rejected, on the other hand, these stocks can potentially play an important role in enhancing the domestic or international diversification gains.

Table 5 reports the *p*-value of the HK statistic denoted by "Joint", for the low-integration portfolio for all investment cases. The null hypothesis of spanning is rejected at any conventional significance level for both the equal- and value-weighted "Low" portfolio, as shown in Panels A and B. Thus, the "Low" portfolio might offer significant diversification benefits when included in a portfolio of domestic, foreign and international market indices.

We also report the *p*-value of the step-down tests of Kan and Zhou (2012), denoted as STD1 and STD2. The *p*-value of STD1 corresponds to the null hypothesis that the two frontiers have the same tangency portfolio while STD2 tests the equality of the global minimum variance portfolio. From a diversification point of view, we are more interested in rejections due to STD2 rather than STD1 since risk reduction is the objective of diversification. In the equal-weighted scheme, the *p*-value of STD1 is almost zero while the *p*-value of STD2 is over 90% for the domestic and international case, meaning that spanning is rejected due to the deviation of the tangency instead of the global minimum variance portfolio. In all other cases including the value-weighted scheme, the step-down tests show that the efficient frontier as a whole has shifted in a statistically meaningful manner. Thus, we expect the low-integration portfolio to offer investors additional diversification benefits when included in a market index strategy.

3.6. Intersection tests: Do low integrated stocks offer better risk-adjusted returns?

The spanning tests of the previous section are promising since the difference in tangency portfolios is the reason that spanning for the low-integration portfolio is rejected. Thus we proceed to test the difference between the maximum Sharpe ratio attainable for several strategies.[8] Our starting point is the S&P 500 as the main domestic asset in a portfolio of a US investor. From there, we examine the effect of including the foreign market indices and the value-weighted low-integration portfolio on the Sharpe ratio of the corresponding tangency portfolio.

The Sharpe ratio test is a mean–variance intersection test that checks whether two efficient frontiers intersect at the tangency point for a given risk-free rate. More formally, we test the equivalence of the two Sharpe ratios using the test of Ledoit and Wolf (2008).[9] The calculation of the *p*-value of their test relies on the construction of confidence intervals from bootstrapped pairs of returns that are not assumed to be normally or independently distributed. The *p*-value is calculated by the frequency in which the value of zero lies inside the bootstrapped confidence intervals.

Panel A of Table 6 reports the *p*-value of the Ledoit and Wolf (2008) test for all the strategies. For completeness, we report the results for both the unconstrained (with short sales) and the constrained (no short sales) problem but our focus is on the latter which

[8] The difference in Sharpe ratios is not the only way to quantify diversification benefits; for example, the portfolio diversification index of Rudin and Morgan (2006) and the modified diversification delta of Flores et al. (2017) are alternative measures of diversification.

[9] Michael Wolf kindly provides Matlab code for the test in his website https://www.econ.uzh.ch/en/people/faculty/wolf/publications.html at the University of Zurich.

Table 4
Risk and return characteristics of integration portfolios.

Panel A: Equal-weighted

	Integration portfolios									
Statistic	Low	2	3	4	5	6	7	8	9	High
Mean	1.60	1.50	1.48	1.43	1.44	1.44	1.42	1.38	1.34	1.35
Std.Dev.	5.99	5.94	5.96	5.95	5.95	6.00	6.07	6.05	6.17	6.57
VaR 95%	6.93	7.69	7.58	7.66	7.72	7.49	7.98	8.15	8.60	8.88
Max.Drawdown	58.31	58.16	58.55	60.03	58.60	58.04	60.55	58.98	57.97	59.43
Sharpe	0.71***	0.67***	0.65***	0.62***	0.63***	0.62***	0.60***	0.58***	0.55***	0.52***
Sortino	1.33	1.18	1.16	1.09	1.11	1.07	1.04	1.00	0.95	0.88
PDI	7.27	7.52	7.51	7.44	7.54	7.47	7.30	7.39	7.16	6.89

Panel B: Value-weighted

	Integration portfolios									
Statistic	Low	2	3	4	5	6	7	8	9	High
Mean	1.21	1.10	1.09	1.14	1.11	1.19	1.20	1.09	1.11	1.09
Std.Dev.	4.73	4.67	4.55	4.54	4.43	4.59	4.55	4.66	5.02	5.29
VaR 95%	6.20	6.50	6.39	6.17	5.73	6.24	6.31	6.72	7.95	7.85
Max.Drawdown	53.92	53.76	51.37	59.31	50.05	54.11	51.97	52.35	57.23	66.70
Sharpe	0.62***	0.55***	0.56***	0.59***	0.59***	0.62***	0.64***	0.54***	0.52***	0.48***
Sortino	1.05	0.93	0.95	0.99	1.00	1.04	1.14	0.89	0.85	0.80
PDI	2.94	3.25	3.24	3.38	3.45	3.50	3.34	3.38	3.58	3.39

Panel C: Global and domestic integration

	Integration deciles									
	Low	2	3	4	5	6	7	8	9	High
R-square	−7.30	−3.52	−0.82	1.77	4.39	7.18	10.29	14.06	19.13	29.49
Dom R-square	2.37	4.53	6.25	8.00	10.09	11.95	14.27	17.22	20.95	26.82

Notes: The table reports the return and risk characteristics for each integration portfolio. Mean, standard deviation and 95% Value-at-Risk are monthly and in percentage while Sharpe (along with their significance levels) and Sortino ratios have been annualized. We report the maximum drawdown of the portfolios in percentages. The Portfolio Diversification Index (PDI) of Rudin and Morgan, 2006 for the integration portfolios is also included. At the start of each calendar year t, we sort stocks into decile portfolios based on their integration measure of the previous year $t-1$, thus forming 10 equal- or value-weighted integration portfolios for the rest of the year. The Low and High portfolios consist of the 10% least and most integrated stocks. Panel A and B correspond to equal- and value-weighted portfolios, respectively. Panel C reports the average global (R-square) and domestic integration level of stocks (Dom R-square) when sorted in deciles based on their R-square measure. The domestic R-square corresponds to the integration level of a US stock with respect to the local market as opposed to foreign markets. R-square values are quoted in percentage. Monthly data from January 1975 to December 2020 have been employed in the analysis.

constitutes a more easily implementable strategy. A purely domestic investor is better off holding the "Low" portfolio instead of the S&P 500 with Sharpe ratios of 0.179 and 0.105, respectively. The null hypothesis that the low-integration portfolio does not increase the Sharpe ratio is rejected at the 1% level when short sales are not allowed in the "S&P500" versus "S&P500+Low" specification. Similarly, an economically and statistically significant difference in the slope of the capital market line at the 10% and 1% level, is observed when the domestic index is augmented with foreign market indices ("S&P500+10TRMIs") or with foreign market indices and low integrated stocks ("S&P500+10TRMIs+Low") which means that holding just the S&P 500 is a sub-optimal strategy.

A traditional approach for US investors to gain additional diversification benefits is to invest in the S&P 500 alongside international market indices such as the TRMIs which begs the question: does the low-integration portfolio offer higher risk-adjusted returns when included in the international index strategy "S&P500+10TRMIs"? The answer is yes when short sales are allowed. The increase of the Sharpe ratio from 0.182 to 0.233 is statistically significant at the 5% level. In the constrained problem an economically significant increase from 0.164 to 0.194 is also observed but it is not statistically significant at conventional levels. Finally, we examine the "S&P500+Low" versus "S&P500+10TRMIs" strategy and we find that the equivalence of the tangency portfolios cannot be rejected with the test generating p-values above 67%. This last finding emphasizes a US investor's capacity to own exclusively domestic assets (the S&P500 and the "Low" portfolio) and generate economically and statistically indistinguishable risk-adjusted returns from a globally diversified index portfolio.

We showed that the low-integration portfolio offers higher risk-adjusted returns in domestic and international index strategies, but is this associated with a reduction in risk? To answer this question, we apply the robust variance test of Ledoit and Wolf (2011) and a paired quantile test to the optimal mean–variance strategies of Table 6. Panel A of Table 7 reports the p-value of the Ledoit and Wolf (2011) test for the tangency portfolios. The most notable finding is that low integrated stocks reduce economically and statistically the variance of the efficient portfolio when included in an international index portfolio; the variance falls from 4.71% to 4.20% with a p-value less than 1%. Additionally, the risk of the purely domestic strategy "S&P500+Low" is the same as that of "S&P500+10TRMIs". However, if short sales are allowed, the former strategy is superior in terms of variance, reducing it from 5.4% to 4.7% with the difference being significant at the 5% level.

As far as tail risk is concerned, Panel A of Table 8 reports the p-value of the paired sign test for the 95% Value-at-Risk of the tangency portfolios. Focusing on the constrained problem, the results are ubiquitous; the inclusion of low integrated stocks decreases

Table 5
Mean–variance spanning tests for the low-integration portfolio.

Panel A: Equal-weighted

Case	α	δ	Joint p-value	STD1	STD2
Domestic	0.008**	0.028	0.000	0.000	0.905
Foreign	0.008**	0.232	0.000	0.000	0.000
International	0.008**	0.043	0.000	0.000	0.976

Panel B: Value-weighted

Case	α	δ	Joint p-value	STD1	STD2
Domestic	0.005**	0.106	0.000	0.000	0.001
Foreign	0.005**	0.340	0.000	0.000	0.000
International	0.004**	0.089	0.000	0.000	0.030

Notes: The table reports the p-values of three Likelihood Ratio tests for mean–variance spanning tests for the domestic, foreign and international case as described in Eqs. (2.2)–(2.4), respectively. In the domestic case, the benchmark asset is the S&P 500. In the foreign case, the benchmark assets are the 10 total return market indices (TRMIs). In the international case, both the S&P 500 and the 10 TRMIs are the benchmark assets. The 10 TRMIs are Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Singapore, Switzerland and United Kingdom. The test asset in all cases is the equal- or value-weighted low-integration portfolio that consists of the 10% least integrated stocks. We report the p-value of the Joint hypothesis ($\alpha = 0$ and $\delta = 0$), STD1 hypothesis ($\alpha = 0$) and STD2 hypothesis ($\delta = 0$ given $\alpha = 0$) in the respective columns. STD1 and STD2 refer to the step-down procedure of Kan and Zhou, 2012. Specifically, STD1 tests the equivalence of the tangency portfolios of the efficient frontiers generated by the benchmark and the augmented assets while STD2 tests the equivalence of their global minimum variance portfolios given that the frontiers intersect at the tangency point. In other words, rejection of STD1 and STD2 implies differences in the tangency and global minimum variance portfolio, respectively. When both STD1 and STD2 are rejected, then the inclusion of the test assets in the benchmark assets moves the efficient frontier in a statistically significant manner. Monthly data from January 1975 to December 2020 have been employed in the analysis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

significantly the tail risk. The most stark difference is found in “S&P500+10TRMIs+Low” and “S&P500+Low”. The first case highlights the importance of the “Low” portfolio in augmenting the international index strategy while the second reveals the power of the pure domestic strategy “S&P500+Low” to present similar downside risk diversification benefits to the “S&P500+10TRMIs” strategy.

To complement the findings of Table 6, we report the optimal mean–variance weights of the tangency portfolio for all efficient frontiers in Table 9. It is evident that both in the unconstrained and constrained case, the low-integration portfolio receives the greater weight when included as a potential investment thus showcasing its superiority in the mean–variance framework. Even though the Sharpe ratios of the benchmark and augmented frontiers in some cases might not be statistically different, low integrated stocks receive over 50% of our capital in almost all strategies.

3.7. Sub-period analysis: Do low integrated stocks offer the same risk-adjusted returns throughout the years?

The previous section establishes that the low integrated stocks do offer better risk-adjusted returns for the period 1975–2020 from which the in-sample tangency portfolios are estimated. However, the integration pattern of firms and industries suggests that the US as a whole became more integrated with global markets after the year of 2000. Thus we suspect that the role of the low-integration portfolio for diversification purposes becomes more important in the second half of our sample period rather than in the first. In order to assess if low integrated stocks show better risk-adjusted results after 2000, we split our sample into 1975–1999 and 2000–2020 and carry out the same analysis as in Section 3.6 for two sub-periods.

Panels B and C of Table 6 reports the Sharpe ratios and the corresponding p-values of the Ledoit and Wolf (2008) test for the in-sample tangency portfolios of the strategies of the previous section for the two sub-periods. Even though the effect of the low integrated stocks on risk-adjusted returns is more prominent in the unconstrained problem, the pattern for the two periods is clear; the effect is not the same. Specifically, the low-integration portfolio offers economically and statistically higher Sharpe ratios after 2000. The most notable differences between the sub-samples are found in the “S&P500” vs “S&P500+Low” case and in the “S&P500+10TRMIs” vs “S&P500+10TRMIs+Low” where the augmentation of the domestic and international index portfolio with the “Low” portfolio yields higher ratios with higher statistical significance. When short sales are allowed, we document an increase from 0.131 to 0.174 (p-value of 13.4%) in 1975–1999 and from 0.074 to 0.185 (p-value of 2.5%) in 2000–2020 when we augment S&P500 with low integrated stocks. When we consider the “S&P500+10TRMIs” vs “S&P500+10TRMIs+Low” strategy, we observe an increase from 0.224 to 0.255 (p-value of 21%) in the first sub-period and from 0.220 to 0.291 (p-value of 5.5%) in the second. The portfolio of S&P 500 and the low integrated stocks is preferable to that of the international index strategy only in 2000–2020

Table 6
Comparison of diversification strategies in terms of their Sharpe ratio.

	Panel A: Period 1975–2020						Panel B: Period 1975–1999						Panel C:Period 2000–2020					
	With Short Sales			No Short Sales			With Short Sales			No Short Sales			With Short Sales			No Short Sales		
	Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio		
Strategy	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + “Low”		0.179	0.002		0.179	0.005		0.174	0.134		0.174	0.128		0.185	0.025		0.185	0.022
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + 10TRMIs		0.182	0.04		0.164	0.06		0.224	0.087		0.211	0.097		0.220	0.024		0.133	0.173
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + 10TRMIs + “Low”		0.233	0.001		0.194	0.001		0.255	0.013		0.225	0.017		0.291	0.003		0.185	0.020
SP&500 + 10TRMIs	0.182			0.164			0.224			0.211			0.220			0.133		
SP&500 + 10TRMIs + “Low”		0.233	0.025		0.194	0.21		0.255	0.210		0.225	0.396		0.291	0.055		0.185	0.327
SP&500 + 10TRMIs	0.182			0.164			0.224			0.211			0.220			0.133		
SP&500 + “Low”		0.179	0.942		0.179	0.677		0.174	0.327		0.174	0.427		0.185	0.574		0.185	0.346

Notes: Table reports the monthly Sharpe ratio and the associated *p*-value of Ledoit and Wolf, 2008 test for several strategies. Each strategy is implemented by the in-sample tangency portfolio of the corresponding assets for the full period 1975–2020 and its sub-periods 1975–1999 and 2000–2020. The test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value reported in the third column (bottom row). For example, the Sharpe ratio of the S&P500 (column (1)) for the full sample period 1975–2000 is 0.105 while that of the S&P500 and the Low portfolio (column (2)) when short sales are allowed is 0.179. The null hypothesis that the Sharpe ratios of the previous strategies are equal is 0.2% (column p-value). All other values are interpreted in the same way. The low-integration portfolio that is denoted as Low contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1975 to December 2020 have been employed in the analysis.

Table 7
Comparison of diversification strategies in terms of their variance.

	Panel A: Period 1975–2020						Panel B: Period 1975–1999						Panel C:Period 2000–2020					
	With Short Sales			No Short Sales			With Short Sales			No Short Sales			With Short Sales			No Short Sales		
	Std.Dev.			Std.Dev.			Std.Dev.			Std.Dev.			Std.Dev.			Std.Dev.		
Strategy	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value
SP500	4.342			4.342			4.290			4.290			4.383			4.383		
SP500 + Low		4.737	0.003		4.737	0.009		4.887	0.009		4.887	0.012		4.550	0.529		4.550	0.507
SP500	4.342			4.342			4.290			4.290			4.383			4.383		
SP500 + 10TRMIs		5.361	0.001		4.705	0.011		4.705	0.001		4.479	0.033		7.255	0.001		4.806	0.036
SP500	4.342			4.342			4.290			4.290			4.383			4.383		
SP500 + 10TRMIs + Low		5.239	0.001		4.177	0.198		5.072	0.004		4.269	0.903		6.143	0.001		4.550	0.530
SP500 + 10TRMIs	5.361			4.705			4.705			4.479			7.255			4.806		
SP500 + 10TRMIs + Low		5.239	0.321		4.177	0.001		5.072	0.001		4.269	0.016		6.143	0.012		4.550	0.378
SP500 + 10TRMIs	5.361			4.705			4.705			4.479			7.255			4.806		
SP500 + Low		4.737	0.018		4.737	0.851		4.887	0.533		4.887	0.144		4.550	0.001		4.550	0.341

Notes: Table reports the monthly standard deviation (%) and the associated *p*-value of Ledoit and Wolf, 2011 test for several strategies. Each strategy is implemented by the in-sample tangency portfolio of the corresponding assets sub-sampled for the full period 1975–2020 and its sub-periods 1975–1999 and 2000–2020. The test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value reported in the third column (bottom row). For example, the standard deviation of the S&P500 (column (1)) for the full sample period 1975–2000 is 4.3% while that of the S&P500 and the "Low" portfolio (column (2)) when short sales are allowed is 4.7%. The null hypothesis that the variances of the previous strategies are equal is 0.3% (column "p-value"). All other values are interpreted in the same way. The low-integration portfolio that is denoted as Low contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1975 to December 2020 have been employed in the analysis.

Table 8
Comparison of diversification strategies in terms of their 95% Value-at-Risk.

	Panel A: Period 1975–2020						Panel B: Period 1975–1999						Panel C:Period 2000–2020					
	With Short Sales			No Short Sales			With Short Sales			No Short Sales			With Short Sales			No Short Sales		
	VaR 95%			VaR 95%			VaR 95%			VaR 95%			VaR 95%			VaR 95%		
Strategy	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value
SP&500	6.672			6.672			5.751			5.751			7.953			7.953		
SP&500 + "Low"		6.203	0.000		6.203	0.000		5.565	0.000		5.565	0.000		6.766	0.000		6.766	0.000
SP&500	6.672			6.672			5.751			5.751			7.953			7.953		
SP&500 + 10TRMIs		7.034	0.000		7.135	0.000		5.690	0.000		5.248	0.000		10.080	0.000		8.309	0.000
SP&500	6.672			6.672			5.751			5.751			7.953			7.953		
SP&500 + 10TRMIs + Low		7.448	0.000		5.895	0.000		5.914	0.000		4.614	0.000		7.336	0.000		6.766	0.000
SP&500 + 10TRMIs	7.034			7.135			5.690			5.248			10.080			8.309		
SP&500 + 10TRMIs + "Low"		7.448	0.000		5.895	0.000		5.914	0.000		4.614	0.000		7.336	0.000		6.766	0.000
SP&500 + 10TRMIs	7.034			7.135			5.690			5.248			10.080			8.309		
SP&500 + "Low"		6.203	0.000		6.203	0.000		5.565	0.000		5.565	0.000		6.766	0.000		6.766	0.000

Notes: Table reports the monthly 95% Value-at-Risk (%) and the associated *p*-value of a non-parametric paired sign test used to test quantiles as described in Conover, 1999 for several strategies. Each strategy is implemented by the in-sample tangency portfolio of the corresponding assets for the full period 1975–2020 and its sub-periods 1975–1999 and 2000–2020. The test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value reported in the third column (bottom row). For example, the 95% Value-at-Risk of the S&P500 (column (1)) for the full sample period 1975–2000 is 6.7% while that of the S&P500 and the "Low" portfolio (column (2)) when short sales are allowed is 6.2%. The null hypothesis that the Value-at-Risk of the previous strategies are equal is less than 0.1% (column "p-value"). All other values are interpreted in the same way. The low-integration portfolio that is denoted as "Low" contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1975 to December 2020 have been employed in the analysis.

Table 9
Optimal mean–variance weights.

	S&P500	S&P500+Low		S&P500+10TRMIs		S&P500+10TRMIs+Low	
Assets		Short	No Short	Short	No Short	Short	No Short
Low-integration		1.000	.1.000			1.000	0.597
SP500	1	0.000	0.000	0.057	0.000	−0.699	0.000
Australia				0.167	0.112	0.124	0.005
Canada				−0.138	0.000	−0.179	0.000
France				0.363	0.066	0.281	0.000
Germany				−0.586	0.000	−0.387	0.000
Hong Kong				0.064	0.017	0.082	0.020
Italy				−0.060	0.000	−0.057	0.000
Japan				−0.101	0.000	−0.013	0.000
Singapore				0.096	0.071	0.032	0.000
Switzerland				0.988	0.624	0.697	0.360
UK				0.151	0.110	0.120	0.018
Portfolio Performance							
Mean(%)	0.818	1.21	1.21	1.336	1.133	1.582	1.172
Std.Dev.(%)	4.342	4.737	4.737	5.361	4.705	5.239	4.177
VaR 95% (%)	6.672	6.203	6.203	7.034	7.135	7.448	5.895
Sharpe	0.105	0.179	0.179	0.182	0.164	0.233	0.194
Sortino	0.171	0.301	0.301	0.327	0.274	0.408	0.314

Notes: The table reports the optimal mean–variance weights of the tangency portfolio for the strategies of Table 6. The Short and No Short columns correspond to the unconstrained and unconstrained problem, respectively. All measures of portfolio performance are of monthly frequency and in percentage form except for the Sharpe and Sortino ratio. Monthly data from January 1975 to December 2020 have been employed in the analysis.

when short sales are not allowed. This finding is consistent with that for the full sample period highlighting again the diversification potential of the "Low" portfolio.

Now we turn our attention to how the portfolio variance of the tangency portfolios of Table 6 behaves. We report the results of the Ledoit and Wolf (2011) test for the difference in variance between strategies in Panels B and C of Table 7. The variance reduction from the inclusion of the low-integration portfolio is more noticeable after 2000. However, no strategy consistently yields lower total risk than the S&P 500. Thus, even though, the low integrated stocks reduce the portfolio variance when included in a strategy, one is better off holding only the US index rather than investing in the other tangency portfolios. However, variance is a faulty measure of risk since downside and upward movements are weighted equally in its calculation.

Finally, all the previous strategies are evaluated in terms of their portfolio tail risk as captured by the Value-at-Risk at the 95% level in Panels B and C of Table 8. The signed paired quantile test rejects the null hypothesis that the 95% VaR of the strategies compared is the same with p-values less than 0.1%. Thus it makes more sense to focus on the economic impact of low integrated stocks on tail risk reduction rather than its statistical significance which has already been established. Two things are clear by calculating the percentage difference of VaR of strategy (2) over (1): (i) the absolute level of tail risk of all strategies is elevated for the second half of our sample and (ii) the percentage reduction of VaR with the inclusion of the low-integration portfolio is much higher for 2000–2020 compared to 1975–1999. For example, the "S&P500+Low" strategy reduces the 95% VaR by 3% before 2000 and by 15% after 2000 for both the unconstrained and constrained problem. The most stark differences are found in the "S&P500+10TRMIs" vs "S&P500+10TRMIs+Low" regime in which tail risk falls by 4% before 2000 and by 27% after 2000 when short sales are allowed.[10] The ability of "S&P500+Low" to yield indistinguishable or better diversification benefits from an international index strategy becomes apparent only after 2000 with VaR reductions of 33% and 18% depending on whether short sales are allowed or not.

4. Robustness checks

We discuss several robustness checks.

4.1. Alternative estimation of the R-square measure

In our baseline model, we calculate the R-square measure using the return matrix of the contemporaneous weekly returns of the 10 developed market indices. In order to alleviate issues regarding the propagation friction in the financial markets, we augment the return matrix with both the lead and lagged weekly returns of the same market indices. We again keep only the first five principal components and, thus, we re-estimate firm-level integration using the lead–lag R-square measure. Value-weighted decile integration portfolios are formed by sorting stocks based on this alternative lead–lag R-square measure.

[10] When there are short sales constraints, the 95% VaR reduction is 12% and 18% for the two sub-periods.

Table 10
Comparison of diversification strategies in terms of their Sharpe ratio for lead–lag R-square measure.

	Panel A: Period 1975–2020						Panel B: Period 1975–1999						Panel C:Period 2000–2020					
	With Short Sales			No Short Sales			With Short Sales			No Short Sales			With Short Sales			No Short Sales		
	Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio		
Strategy	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value	(1)	(2)	*p*-value
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + "Low"		0.160	0.013		0.160	0.014		0.150	0.499		0.150	0.491		0.171	0.004		0.171	0.005
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + 10TRMIs		0.182	0.036		0.164	0.055		0.226	0.094		0.213	0.096		0.225	0.013		0.135	0.154
SP&500	0.105			0.105			0.131			0.131			0.074			0.074		
SP&500 + 10TRMIs + "Low"		0.217	0.002		0.182	0.002		0.240	0.030		0.220	0.020		0.283	0.001		0.172	0.009
SP&500 + 10TRMIs	0.182			0.164			0.226			0.213			0.225			0.135		
SP&500 + 10TRMIs + "Low"		0.217	0.096		0.182	0.359		0.240	0.486		0.220	0.644		0.283	0.057		0.172	0.403
SP&500 + 10TRMIs	0.182			0.164			0.226			0.213			0.225			0.135		
SP&500 + "Low"		0.160	0.580		0.160	0.921		0.150	0.176		0.150	0.273		0.171	0.341		0.171	0.485

Notes: Table reports the monthly Sharpe ratio and the associated *p*-value of Ledoit and Wolf, 2008 test for several strategies when integration portfolios are formed based on the lead–lag R-square measure. Each strategy is implemented by the in-sample tangency portfolio of the corresponding assets for the full period 1975–2020 and its sub-periods 1975–1999 and 2000–2020. The test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value reported in the third column (bottom row). For example, the Sharpe ratio of the S&P500 (column (1)) for the full sample period 1975–2000 is 0.105 while that of the S&P500 and the Low portfolio (column (2)) when short sales are allowed is 0.160. The null hypothesis that the Sharpe ratios of the previous strategies are equal is 1.3% (column p-value). All other values are interpreted in the same way. The low-integration portfolio that is denoted as Low contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1975 to December 2020 have been employed in the analysis.

Table 11
Comparison of diversification strategies in terms of their Sharpe ratio for out-of-sample global minimum variance portfolios for 1978–2020.

	With Short Sales			No Short Sales		
	Sharpe Ratio			Sharpe Ratio		
Strategy	(1)	(2)	*p*-value	(1)	(2)	*p*-value
SP&500	0.109			0.109		
SP&500 + "Low"		0.133	0.024		0.145	0.008
SP&500	0.109			0.109		
SP&500 + 10TRMIs		0.112	0.704		0.141	0.474
SP&500	0.109			0.109		
SP&500 + 10TRMIs + "Low"		0.119	0.717		0.158	0.039
SP&500 + 10TRMIs	0.112			0.141		
SP&500 + 10TRMIs + "Low"		0.119	0.343		0.158	0.029
SP&500 + 10TRMIs	0.112			0.141		
SP&500 + "Low"		0.133	0.501		0.145	0.865

Notes: Table reports the monthly Sharpe ratio and the associated *p*-value of Ledoit and Wolf, 2008 test for several out-of-sample global minimum variance strategies for the period 1978–2020. At the end of each calendar year, we invest in the global minimum variance portfolios and hold the position for 12 months. A rolling window of 60 months is employed for the estimation of the historical covariance matrix. The test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value reported in the third column (bottom row). For example, the Sharpe ratio of the S&P500 (column (1)) is 0.109 while that of the S&P500 and the Low portfolio (column (2)) when short sales are allowed is 0.133 . The null hypothesis that the Sharpe ratios of the previous strategies are equal is 2.4% (column p-value). All other values are interpreted in the same way. The low-integration portfolio that is denoted as Low contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1978 to December 2020 have been employed in the analysis.

Table 10 reports the *p*-value of the test of Ledoit and Wolf (2008) for all the strategies. The results are consistent with the baseline model. Investment in the S&P500 only is sub-optimal. Investors gain economically and statistically significant diversification benefits when they hold both the S&P500 and the low-integration portfolio for the full period 1975–2020 and the second sub-period 2000–2020. Home-made diversification benefits still hold except for the first sub-period 1975–1999 as it was the case for our base results. In the previous millennium, the monthly Sharpe ratio of the "S&P500+10TRMIs" is higher in both the unconstrained and constrained problem (0.226 and 0.213, respectively) than the Sharpe ratio of the "S&P500+Low" strategy (0.150 and 0.150, respectively) but they are not statistically different (p-values of 17.6% and 27.3%).

4.2. Intersection tests for out-of-sample diversification strategies

We have already established that the low integration portfolio offers additional diversification potential by constructing in-sample tangency portfolios. To evaluate the attractiveness of the "Low" portfolio for investors who wish to follow this strategy in real life, we perform out-of-sample tests. Jagannathan and Ma (2003) argue that the global minimum variance (GMV) portfolio performs better than the tangency portfolio out of sample; the estimation error in the calculation of mean returns is so large that portfolios formed only on the basis of the covariance matrix of returns are superior. For that reason, we opt for GMV portfolios instead of tangency portfolios for out-of-sample tests. At the end of each calendar year, we invest in the global minimum variance portfolios and hold the position for 12 months. A rolling window of 60 months is employed for the estimation of the historical covariance matrix.

Table 11 reports the *p*-value of the test of Ledoit and Wolf (2008) for all the strategies when out-of-sample global minimum variance portfolios are employed in the analysis. It is clear that the levels of the monthly Sharpe ratio are lower than those of the in-sample tangency portfolios; this is the difference between ex-post and ex-ante Sharpe ratios and it is to be expected. When short sales are used, holding only the S&P500 is a slightly sub-optimal strategy in terms of the economical and statistical significance of the difference in Sharpe ratios. Even though the "S&P500+Low" strategy yields a monthly Sharpe ratio of 0.133 that is higher than that of the "S&P500+10TRMIs" (0.112), the *p*-value of the test is 50%. On the contrary when short sales are not allowed, the inclusion of the low-integration portfolio in all strategies yields to economically and statistically significant increases in the risk-adjusted returns. The home-diversification benefits that investors reap from the "S&P500+Low" strategy are indistinguishable from those of the international strategy "S&P500+10TRMIs" supporting the role of the low integrated stocks in that regard.

4.3. Intersection tests in crisis and non-crisis periods

Our extensive time series of returns allows us to study the diversification potential of the low-integration portfolio in crisis and non-crisis periods. Table 12 reports the US NBER crisis periods that are used in the analysis. The months that lie outside of the union of the crisis periods of Table 12 define the non-crisis periods. For our 1975–2020 sample, the crisis period amount to 64 monthly observations.

Table 13 reports the difference in Sharpe ratios and the associated *p*-value of the Ledoit and Wolf (2008) test for all the strategies in crisis and non-crisis periods. We only apply the Ledoit and Wolf (2008) test when we compare positive Sharpe ratios. The ranking

Table 12
Outline of NBER US crisis periods.

Crisis	Start of crisis period	End of crisis period	Duration (months)
Oil Embargo Recession	Nov 1973	Mar 1975	16
Iran and Volcker Recession	Jan 1980	Jul 1980	6
Double-Dip Recession	Jul 1981	Nov 1982	16
Gulf War Recession	Jul 1990	Mar 1991	8
Dot-Com Recession	Mar 2001	Nov 2001	8
The Great Recession	Dec 2007	Jun 2009	18
COVID-19 Recession	Feb 2020	Apr 2020	2

Notes: The table lists the US NBER crises for the period of January 1975–December 2020 along with start and end dates.

Table 13
Comparison of diversification strategies in terms of their Sharpe ratio for crisis vs non-crisis periods.

	Panel A: Crisis periods						Panel B: Non-crisis periods					
	With Short Sales			No Short Sales			With Short Sales			No Short Sales		
	Sharpe Ratio			Sharpe Ratio			Sharpe Ratio			Sharpe Ratio		
Strategy	(1)	(2)	Difference	(1)	(2)	Difference	(1)	(2)	Difference	(1)	(2)	Difference
SP&500	−0.158			−0.158			0.162			0.162		
SP&500 + Low		−0.112	0.045		−0.112	0.045		0.247	0.085***		0.247	0.0847***
SP&500	−0.158			−0.158			0.162			0.162		
SP&500 + 10TRMIs		0.187	0.345		−0.092	0.066		0.257	0.094		0.249	0.087
SP&500	−0.158			−0.158			0.162			0.162		
SP&500 + 10TRMIs + Low		0.208	0.366		−0.092	0.066		0.318	0.156***		0.284	0.122***
SP&500 + 10TRMIs	0.187			−0.092			0.257			0.249		
SP&500 + 10TRMIs + Low		0.208	0.021		−0.092	0.000		0.318	0.062**		0.284	0.035
SP&500 + 10TRMIs	0.187			−0.092			0.257			0.249		
SP&500 + Low		−0.112	−0.300		−0.112	−0.020		0.247	−0.010		0.247	−0.002

Notes: Table reports the monthly Sharpe ratio and the associated difference of Sharpe ratio for several strategies in crisis and non-crisis periods during Jan 1975–Dec 2020. Each strategy is implemented by the in-sample tangency portfolio of the corresponding assets for crisis and non-crisis periods. Details on the crisis periods are found in Table 12. The Ledoit and Wolf, 2008 test is applied to the pair of strategies (1) (top row) and (2) (bottom row) with the *p*-value being denoted as an asterisk in the difference of the Sharpe ratio of strategy (2) and strategy (1) in the third column (bottom row). *, ** and *** correspond to significance levels of 10%, 5% and 1%, respectively. We only perform the Ledoit and Wolf, 2008 test when both Sharpe ratios are positive. For example, the Sharpe ratio of the S&P500 (column (1)) for non-crisis periods is 0.162 while that of the S&P500 and the Low portfolio (column (2)) when short sales are allowed is 0.247. Their difference is 0.085 (column Difference) and the null hypothesis that the Sharpe ratios of the previous strategies are equal is less than 0.1%. All other values are interpreted in the same way. The low-integration portfolio that is denoted as Low contains the bottom 10% least globally integrated US stocks and it is value-weighted. Monthly data from January 1975 to December 2020 have been employed in the analysis.

between negative–negative and positive–negative Sharpe ratios is ambiguous (see for example Israelsen, 2005). When two assets have the same negative mean return, the one with the higher volatility will have a less negative Sharpe ratio so the other asset is implicitly penalized for its low volatility. The results for the non-crisis periods are quantitatively stronger than the baseline ones. The levels of the Sharpe ratio of all strategies increase when crisis periods that are periods of negative returns and high volatility are excluded from the analysis. The inclusion of the low-integration portfolio in all strategies yields economically and statistically higher risk-adjusted returns. The home-diversification benefits that are captured from investing in the “S&P500+Low” strategy are again indistinguishable from those of the international strategy of “S&P500+10TRMIs”.

5. Conclusion

In this paper, we measure integration at the firm-level for all US publicly listed and traded stocks using the Pukthuanthong and Roll (2009) methodology for the period 1974–2020. We find that US stocks are becoming more integrated with the world as time elapses. While the positive trend holds for all industries, some such as Steel, Coal, Chemicals or Automobiles experience integration at a high rate whereas others such as Games, Food or Healthcare are becoming integrated at a slower pace. There is always a subset of firms that consistently exhibit a low level of integration with foreign markets and, as such, it is immune to shocks originating outside of the US. We argue and show that these low integrated firms that are minimally affected by global economic environment constitute the ideal choice for US investors who wish to gain diversification benefits within developed markets.

First, we show that the low-integration portfolio that contains the bottom 10% least globally integrated US stocks is not spanned by domestic and foreign market indices of developed countries and thus it should offer additional diversification benefits when added to index only strategies. Then we find that the low-integration portfolio offers higher risk adjusted returns when added to an international portfolio that includes the S&P500 and the 10 foreign indices of the most developed countries. In the mean–variance framework, the power of the low integrated US stocks is their ability to increase Sharpe ratios and reduce tail portfolio risk as captured by the 95% Value-at-Risk. A US investor who holds the purely domestic assets of S&P 500 and the "Low" portfolio optimally combined to maximize the Sharpe ratio, can achieve diversification benefits that are equal or better than those from an international index strategy. The diversification effect is stronger after the year 2000 when the US market became more integrated with the world. Finally, domestic portfolios of low integrated stocks offer superior risk advantages than portfolios of high integrated stocks with the latter behaving like an index such as the S&P 500.

Our results have important implications for academics and practitioners. The role of the low integrated stocks that, by definition, are least driven by foreign market shocks to diversification is highlighted in two aspects. First, the low-integration portfolio can enhance international diversification strategies suggesting that even among developed markets in the 21st century there are still significant benefits to be gained. Second, the indistinguishable performance of the combination of the low-integration portfolio along with the S&P500 against an international strategy offers another solution to the "home bias" puzzle. In essence, US investors can mimic the diversification gains of an international investment by holding only domestic assets such as the S&P500 and the low-integration portfolio without investing in foreign assets. Our out-of-sample robustness tests ensure that these strategies are implementable in real life and thus investors can actually benefit from investing in them.

CRediT authorship contribution statement

Thomas Conlon: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing. **John Cotter:** Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing. **Ioannis Ropotos:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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