Should employers pay their employees better?
An asset pricing approach

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ABSTRACT

We uncover a new anomaly in asset pricing that is linked to the remuneration: the more a company spends on salaries and benefits per employee, the better its stock performs, on average. Moreover, the companies adopting similar remuneration policies share a common risk, which is comparable to that of the value premium. For this purpose, we set up an original methodology that uses firm financial characteristics to build factors that are less correlated than in the standard asset pricing methodology. We quantify the importance of these factors from an asset pricing perspective by introducing the factor correlation level as a directly accessible proxy of eigenvalues of the correlation matrix. A rational explanation of the remuneration anomaly involves the positive correlation between pay and employee performance.

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I. Introduction

Should employers pay their employees better? Although this question might appear provoking because lowering production costs remains a cornerstone of the contemporary economy, we present the first attempt to report the real effects of employee remuneration on asset pricing. Remuneration – defined as the annual salaries and benefits expenses (e.g., wages, bonuses, pension expenses, health insurance payment, etc.) per employee – is the basis of any employment contract. For instance, pay was shown to explain, on average, 65% of the variance in evaluations of overall job attractiveness (Rynes et al., 1983). Classical theory states that profit-maximizing firms choose the level of labor pay by setting the marginal cost of labor (i.e., the wage rate) equal to the marginal revenue product of labor (i.e., the marginal benefit). Beyond this paradigm, we provide strong evidence that firms that pay their employees better tend to over-perform on the stock market.

Our objective is to examine whether remuneration is an anomaly that can be priced in asset pricing models. Schwert (2003) defines anomalies as “empirical results that seem to be inconsistent with maintained theories of asset-pricing behavior (the CAPM). They indicate either market inefficiency (profit opportunities) or inadequacies in the asset-pricing model. After they are documented and analyzed in the academic literature, anomalies often seem to disappear, reverse, or attenuate.” Anomalies are typically identified either by regressing a cross-section of average returns (e.g., the seminal Fama and MacBeth (1973) approach uses the capitalization and book-to-market values), or by using a panel regression of the cross-section of returns with different factor returns through the F-Statistic (Gibbons et al., 1989), or by using a portfolio-based approach that segregates individual stocks with similar capitalization and book-to-market values into different style portfolios (Fama and French, 1993). In the latter case (which we refer to as the “FF approach”), the factors formed on small minus big market capitalization portfolios (SMB) and high minus low book-to-market portfolios (HML) explain an important part of the identified anomalies (Fama and French, 1996). Over recent decades, the growing number of discovered anomalies suggests that the standard asset pricing models fail to explain much of the cross-sectional variation in average stock returns. Meanwhile, the effect of remuneration on company performance has surprisingly never been tested, despite the fact that employers pay particular attention to labor costs in attempting to maximize profits.

This research contributes empirically to the asset pricing literature by introducing an observable firm characteristic, namely the remuneration, as a candidate anomaly. More precisely, we focus on remuneration as a priced factor. Indeed, it remains unclear how far remuneration can explain the cross-section of returns despite a sizeable literature on
labor economics that relates labor to asset pricing. This branch of literature has intensively investigated the impact of labor decisions on the firm’s value, notably through the operating leverage, which affects the equity returns riskiness. However, to our best knowledge, there are no asset pricing studies that incorporate employee’s wages as a pricing factor. Besides, based on the impressive list of anomalies analyzed by Harvey et al. (2015), we find only one paper that highlights income as a potential factor. Indeed, Gomez et al. (2015) analyze the relation between U.S. census division-level labor income and the cross-section of returns using the standard Fama and French (1993) approach. More specifically, these authors use per capita personal income (from the Bureau of Economic Analysis) as a new candidate factor and conclude that the cross-section of stock returns depends on the census district in which the headquarters of the firm are located. Unfortunately, as Harvey et al. (2015) has noted, “most of the division level labor income have a non-significant t-statistic. We do not count their factors”. Moreover, we use remuneration at the company level to generate results that are more realistic from an asset pricing perspective, which contrasts with Gomez et al. (2015), whose scope is limited to income per state and per division.

This research contributes also theoretically to the asset pricing literature by introducing a new methodology to build factors that is conceptually close to principal component analysis (PCA) but goes beyond its noise-induced limitations. This methodology presents many advantages compared with the conventional multi-factor approach developed by Fama and French (1992, 1993). We propose a new measure of “explanatory power” of factors where the relevance of the factor does not depend on the number of considered factors, in contrast to the R-squared argument of the FF setting. Hence, we introduce the Factor Correlation Level (FCL) as a metrics of common risks that measures the ability of stocks within the factor to fluctuate in a common way. Importantly, it allows ordering the factors according to their capacity of taking into account the variability of stocks, and therefore to their importance from an asset pricing perspective. In this respect, our ranking by the FCL indicator resembles principal component analysis. At the same time, this indicator is also linked to the R-squared value of the factor in the asset pricing model: higher FCLs correspond to higher R-squared values in the asset pricing model with one factor. The empirical validation of the FCL methodology is founded on an exhaustive testing protocol. First, we use ten factors that summarize most of the existing factors: dividend, capitalization, liquidity, momentum, low-volatility, debt-to-book, sales-to-market, book-to-market, cash and, of course, the remuneration factor; those which are not present in this list remain correlated with some of these factors; we check that performance associated with the remuneration factor is not explained by other major factors such as low-volatility, capitalization, book-to-market, or momentum. Second, we consider six “supersectors” that are used to split stocks into comparable groups
since remuneration varies strongly from one sector to another. Third, we employ a large data set of 3612 daily single stock close prices from January 2001 to July 2015 for the 569 biggest companies in Europe. For comparison, we also treat the same number of randomly selected companies in the U.S.A. whose capitalization exceeds 1 billion of dollars. Although we do not access the remuneration data for these companies, the analysis of other factors allows us to validate the FCL methodology on the U.S. market (often considered as a benchmark) and to compare our predictions to whose of the FF approach. Fourth, we perform several robustness checks to examine if the results change with the tested variations; for instance, we perform a separate analysis with the 258 biggest companies from U.K. to check for potential domestic biases; we also run the methodology on monthly data to check the role of time scale; in the spirit of comparability, we evaluate the factor performances with seven incremental transitions from the standard FF approach to our methodology. Finally, we compare our results with the basic PCA and illustrate its limitations. Our main result indicates that a market neutral investment strategy based on the remuneration anomaly would likely deliver positive annual returns of 2.42% above the market.

The remainder of the paper is organized as follows. Section II offers a literature review that covers several fields of research. Section III describes the novel methodology. Section IV presents the data, whereas Section V presents the empirical results. Section VI discusses the advantages and limitations of our methodology and compares it with the FF approach. Section VII summarizes the main findings and concludes.

II. Literature review

A. The asset pricing

This article is mainly related to the asset pricing literature in which previous studies have shown that the average returns of common stocks are related to firm characteristics such as capitalization, price-earnings ratio, cash flow, book-to-market, past sales growth and past returns. For example, stocks with lower market capitalization tend to have higher average returns (Banz 1981). Another important anomaly is the value premium: value stocks have higher returns than growth stocks, which is likely because the market undervalues distressed stocks (Fama and French 1998). More precisely, small stocks and value stocks have higher average returns than their betas can explain (Campbell and Vuolteenaho 2004). Profitability and investment also add to the description of average returns (Fama and French 2015). The low volatility anomaly was revealed for medium and big stocks in addition to growth stocks (Jordan and Riley 2013). Those stocks that are expected to have high idiosyncratic risk earn
high returns in the cross-section (Fu 2009). This result contradicts previous findings made by Ang et al. (2006), who posit that stocks with high idiosyncratic volatility have low average returns. Macroeconomic risk has also been connected with the cross-section of returns. For instance, the growth rate of industrial production is seen as a priced risk factor in standard asset pricing tests (Chen et al. 1986; Liu and Zhang 2008). There is a size effect in bank stock returns that differs from the market capitalization effects documented in non-financial stock returns (Gandhi and Lustig 2015). The most popular anomaly is momentum: stocks with low past returns tend to have low future returns while stocks with high past returns tend to have high future returns (Jegadeesh and Titman 1993). Hence, the momentum strategy that buys past winners and sells past losers should earn abnormal returns in upcoming years. Return momentum has also been observed when spreads in average momentum returns decrease from smaller to bigger stocks (Fama and French 2012). However, momentum strategies seem to produce losses specifically in January (Jegadeesh and Titman 1993), probably based on taxation effects (Grinblatt and Moskowitz 2004). Similarly, changes in book equity appear to be more informative about expected stock returns than price returns (Bali et al. 2013). Notably, certain stock market anomalies may appear and then disappear after publication in academic journals (McLean and Pontiff 2015). In spite of the abundant literature, the work by Gomez et al. (2015) seems to be the sole article that considers income as a candidate anomaly although it is still not an income per employee but rather per state and per division. Several models have been developed to provide economic interpretations of numerous stylized anomalies and to improve the performance of the CAPM. Simultaneously, the anomaly-based evidence against the CAPM has been questioned because anomalies have primarily been confined to small stocks (Cederburg et al. 2015).}

1 Campbell and Vuolteenaho (2004) introduced a two-beta model to explain the capitalization and book-to-market value anomalies in stock returns by splitting the CAPM into a cash-flow beta with a higher price of risk than a discount-rate beta. Fama and French (1993) proposed a three-factor model to capture the patterns in U.S. average returns associated with capitalization and value-versus-growth. Even after a theoretical rationale for the three-factor model was provided by Ferguson and Shockley (2003), many anomalies remain unexplained by the three-factor model (Fama and French 2015). Although a four-factor model has been derived (Carhart 1997), it has also failed to absorb all the momentum in U.S. average stock returns (Avramov and Chordia 2006). Recently, a five-factor model was introduced to capture capitalization, value, profitability, and investment patterns in average stock returns and is reputed to perform better than the three-factor model (Fama and French 2015).

2 In line with this criticism, doubt was cast on the set of anomalies to consider in a multi-factorial setup, given that Harvey et al. (2015) have summarized 316 potential factors by reviewing 313 papers published since 1967. In the same vein, 38 out of 80 potential firm-level anomalies were shown to be insignificant in the broad cross-section of average stock returns (Hou et al. 2015). In addition, mistakes can easily be made in this field due to multiple testing or data mining methods. As noted by Harvey and Liu (2015), many discovered factors are likely to be false if their t-statistics do not exceed 3. Finally, these papers suggest that many claims in the anomalies literature are likely to be exaggerated regarding the associated t-statistics.
B. Corporate finance

This article is also related to the extensive literature on corporate finance, which has also continued to investigate the relation between remuneration and performance, although it has usually focused on managerial pay as opposed to the broader category of employees that we consider in the present study. This branch of literature typically examines the wage as a managerial incentive likely to reduce agency costs by designing an optimal job contract. In that sense, we may consider that solving the incentive problem leads to shareholder value creation affecting stock returns. Indeed, managers face both discipline and opportunities provided by the free market economy that leads to the notion that there is no need for explicit contracts to resolve incentive problems (Fama 1980). Nevertheless, market forces cannot act as a complete substitute for contracts (Holmstrom 1999) because career concerns must be considered to design optimal contracts and to arrive at strong incentives (Gibbons and Murphy 1992). The effects of incentives depend on how they are designed (Gneezy et al. 2011), given that managers have considerable power to shape their own pay arrangements – and perhaps to even hurting shareholder interest (Bebchuk et al. 2002). Indeed, public company disclosures do not provide a comprehensive measure of managerial incentive to increase shareholder value (O’Byrne and Young 2010). Many explanations were brought forward to justify top managers’ remuneration. Firms with abundant investment opportunities pay their executives better (Gaver and Gaver 1995). The increase in the level of stock-option compensation can be explained by the inability of boards to evaluate its real costs (Hall and Murphy 2003; Jensen et al. 2004). The capitalization of large firms explains many patterns in top manager pay across firms, over time, and between countries (Gabaix and Landier 2008). Manager fixed effects, interpreted as unobserved managerial attributes and understood as a proxy for latent managerial ability, are important in explaining the level of executive remuneration (Graham et al. 2012). Overall, remuneration matters because it may affect a corporation’s level of risk as bonus-driven remuneration might encourage excessive risk-taking. However, pay and risk are correlated not because mis-aligned pay drives risk-taking, but rather because principal agent theory predicts that riskier but more profitable firms must pay more remuneration than less risky firms to provide a risk-averse manager the same incentives (Cheng et al. 2015).

C. Labor economics

The labor economics literature treats this question through the “efficiency wage theory” by relating it to unemployment. Yellen (1984) and Akerlof and Yellen (1990) did a remarkable work with an analysis that is built – unlike most economic models – mainly on sociology
and psychology with experimentation that delivers salient stylized facts on human behavior in a working context. Efficiency wage theory maintains that rising wages is the best way to increase output per employee because it links pecuniary incentives to employee performance. In particular, the use of performance pay packages by employers has been shown to increase employee productivity (Lazear, 2000) and job satisfaction (Green and Heywood, 2008). There are several interesting studies that relate labor market to asset pricing. All these empirical results emphasize the significant impact of labor decisions, in which wage plays a prominent role, onto firm’s value. Santos and Veronesi (2006) show that labor income to consumption ratio is a strong predictor of long horizon returns. Danthine and Donaldson (2002) explain that operating leverage is more significant for the riskiness of equity returns than financial leverage. In other words, attention should be paid to wages, particularly because the priority nature of wages enhances the risk of dividends. In this spirit, Kuehn et al. (2013) note that a high value of unemployment makes wages inelastic, which gives rise to operating leverage. The impact of inelastic wages is even stronger in bad times as it amplifies the equity risk premium. Gourio (2007) argues that because wages are smooth, revenues are more cyclic than costs, making the profits more volatile. In particular, firms with high book-to-market or with low productivity, i.e. value firms, have more pro-cyclic earnings. Ochoa (2013) finds a positive and statistically significant relation between the reliance on skilled labor and expected returns. In times of high volatility, firms with a high share of skilled workers earn an annual return of 2.7% above those with a high share of unskilled workers notably because their labor is more costly to adjust. Labor decisions made by workers can affect firm risk (Donangelo, 2014) while hiring decisions can also be the determinants of firm risk (Carlson et al. 2004; Belo et al. 2014). Indeed, Donangelo (2014) discusses the idea that mobile workers carry some of the firm’s capital productivity when they leave an industry. He finds that portfolios that hold long positions in stocks of high-mobility industries (general workers) and short positions in stocks of low-mobility industries (industry-specific workers) earn an annual return spread of over 5%. Like Monika and Yashiv (2007) who explain that labor should matter since firms’ market value embodies the value of hiring, Belo et al. (2014) argue that the market value of a firm reflects the value of its labor force because the firm can extract rents as compensation for the costs associated with adjusting its labor force. They find that long positions in stocks of low-hiring firms and short positions in high-hiring firms earn an average annual excess stock return of 5.6%. Favilukis and Xiaoji (2016) introduce infrequent renegotiation in standard wages model showing that it leads to smooth average wages. Due to this wage rigidity, they find that wage growth forecasts long-horizon excess equity returns.
D. Social sciences

This article is also broadly related to several streams of research in various social sciences, including sociology, psychology and human resources. In these fields, wage acts like a motivator since it typically reflects a social preference for rewards likely to affect the employee’s performance. Sociological studies have developed a theory of social exchange in which there are equivalent rewards on both sides (Blau 1955), which is consistent with the preference for reciprocity that is viewed as a social preference, as it depends on the behavior of the reference person (Fehr and Falk 2002). Reciprocity induces agents to cooperate voluntarily with the principal when the principal treats them correctly; the evidence for reciprocity is based on a so-called gift exchange experiment.

Psychological studies highlight the exchange in working situations in which the perceived value of labor equals the perceived value of remuneration, based on the theory of equity (Adams 1963). When there is no mismatch between effort and wages, employees may change their perceived effort and even their perceived level of remuneration by redefining the non-pecuniary component.

Human resources studies generally offer evidence that money is an important motivator for most people (Rynes et al. 2004), as pay can help climbing on the Maslow’s motivational hierarchy of needs, including social esteem and self-actualization. Nevertheless, tangible rewards might also produce secondary negative effects on motivation (Baker 1992) by fore-stalling self-regulation (Deci et al. 1999).

III. Methodology

In this section, we introduce a new methodology to build factors that combines advantages of the PCA and the Fama and French (1993) approach. As would be the case with the PCA, our factors are built to be uncorrelated with the market index and with sectorial factors. For each factor, we introduce and estimate the Factor Correlation Level (FCL) that allows us to order the factors based on their importance and to select the most important ones in asset pricing models.

A. Conventional diagonalization of the covariance and correlation matrices

Identifying common risks of multiple assets is necessary to diversify investments and can help to profit from style’s arbitrage opportunities. Conventional approaches, such as PCA, attempt to diagonalize the empirical covariance (or correlation) matrix of the traded universe, i.e., to decorrelate assets by constructing independent linear combinations (portfolios)
of assets. Each eigenvector of the covariance matrix represents the coefficients of one such combination while the corresponding eigenvalue gives its variance. If the covariance matrix does not contain negative elements (i.e., if there are no negatively correlated assets), the eigenvector corresponding to the largest eigenvalue has positive elements that can be interpreted as relative weights of stocks in the market mode. The classical long portfolio, following the market, can be constructed by investing in proportion to these weights. In turn, market neutral portfolios should be orthogonal to the market mode and therefore have both long and short positions (the latter corresponding to negative weights). The other eigenvectors capture different common risks of the traded universe, and the most common include sectorial risks (e.g., banking sector, commodities, energy, etc.).

In mathematical terms, if the covariance matrix $\Omega$ of stocks was known precisely, it might be diagonalized to identify uncorrelated linear combinations of stocks and their variances to assess the related risks. For a traded universe with $n$ stocks, let $r_1, \ldots, r_n$ denote the daily returns of these stocks at a given time. The covariance matrix has $n$ eigenvalues $\lambda_1, \ldots, \lambda_n$ and $n$ eigenvectors $V_1, \ldots, V_n$ satisfying $\Omega V_\alpha = \lambda_\alpha V_\alpha$ (for each $\alpha = 1, \ldots, n$). Each eigenvector $V_\alpha$ determines one linear combination of stocks, $(V_\alpha)^T r_1 + \ldots + (V_\alpha)^T r_n$, which is decorrelated from the others, while the eigenvalue $\lambda_\alpha$ is its variance (under the condition that $V_\alpha$ is appropriately normalized).

The above eigenbasis can be interpreted as follows. For any linear combination of stocks with weights $w_i$, $r_\pi = w_1 r_1 + \ldots + w_n r_n = (w \cdot r)$ (written as a scalar product), the variance of such a portfolio $\pi$ can be expressed as

$$\langle r_\pi^2 \rangle = \left( \sum_{i=1}^{n} w_i r_i \right)^2 = \sum_{i,j=1}^{n} w_i w_j \Omega_{i,j} = \sum_{i,j=1}^{n} w_i w_j \sum_{\alpha=1}^{n} \lambda_\alpha (V_\alpha)_i (V_\alpha)_j = \sum_{\alpha=1}^{n} \lambda_\alpha (w \cdot V_\alpha)^2, \quad (1)$$

where $\langle \ldots \rangle$ denotes the expectation, and the returns $r_k$ were assumed to be centered. In other words, the variance is decomposed into a sum of variances $\lambda_\alpha$ of independent linear combinations proportional to the projection of the weights $w_i$ onto the corresponding eigenvector $V_\alpha$. If the weights $w_i$ are chosen in proportion to the elements of one eigenvector, i.e., $w_i = c (V_\alpha)_i$ for some $\alpha$ and $c$, then the orthogonality of $V_\alpha$ to other eigenvectors yields

$$\langle r_\pi^2 \rangle = \lambda_\alpha c^2 (V_\alpha \cdot V_\alpha)^2 = \lambda_\alpha (w \cdot w), \quad (2)$$

where we used the $L^2$-normalization of the eigenvectors: $(V_\alpha \cdot V_\alpha) = 1$. As expected, the variance of such a linear combination is fully determined by the corresponding eigenvalue.
\[ \lambda_\alpha = \frac{\langle r_\pi^2 \rangle}{\sum_{i=1}^n w_i^2} \]  

(3)

to estimate the variance of the linear combination whose weights are constructed close to an eigenvector.

As different stocks exhibit quite distinct volatilities, it is convenient to rescale the stock’s return \( r_i \) by its realized volatility \( \sigma_i \): \( \tilde{r}_i = r_i / \sigma_i \). This rescaling is also known to reduce heterogeneity of volatilities among stocks and heteroskedasticity (Andersen et al. 2000; Bouchaud et al. 2001; Valeyre et al. 2013). In other words, one can write

\[ \langle r_\pi^2 \rangle = \sum_{i,j=1}^{n} \tilde{w}_i \tilde{w}_j C_{i,j}, \]  

(4)

where \( \tilde{w}_i = w_i \sigma_i \) and \( C = \langle \tilde{r}_i \tilde{r}_j \rangle \) is the covariance matrix of the renormalized returns \( \tilde{r}_i \) or, equivalently, the correlation matrix of returns \( r_i \): \( \Omega_{i,j} = \sigma_i \sigma_j C_{i,j} \). To proceed, the eigenvalues and eigenvectors of \( \Omega \) can be replaced by the eigenvalues \( \tilde{\lambda}_\alpha \) and eigenvectors \( \tilde{V}_\alpha \) of the correlation matrix \( C \), \( C \tilde{V}_\alpha = \tilde{\lambda}_\alpha \tilde{V}_\alpha \), i.e.,

\[ \langle r_\pi^2 \rangle = \sum_{i,j=1}^{n} \tilde{w}_i \tilde{w}_j \sum_{\alpha=1}^{n} \tilde{\lambda}_\alpha \tilde{V}_\alpha_i \tilde{V}_\alpha_j = \sum_{\alpha=1}^{n} \tilde{\lambda}_\alpha (\tilde{w} \cdot \tilde{V}_\alpha)^2. \]  

(5)

If the volatility-normalized weights \( \tilde{w}_i \) are chosen to be proportional to the elements of an eigenvector, \( \tilde{w}_i = c(V_\alpha)_i \), one obtains \( \langle r_\pi^2 \rangle = \tilde{\lambda}_\alpha c^2 (\tilde{V}_\alpha \cdot \tilde{V}_\alpha) = \tilde{\lambda}_\alpha c^2 = \tilde{\lambda}_\alpha (\tilde{w} \cdot \tilde{V}_\alpha) \), from which

\[ \tilde{\lambda}_\alpha = \frac{\langle r_\pi^2 \rangle}{\sum_{i=1}^n w_i^2 \sigma_i^2}; \]  

(6)

where the \( L^2 \)-normalization of \( \tilde{V}_\alpha \) was used: \( (\tilde{V}_\alpha \cdot \tilde{V}_\alpha) = 1 \). As previously discussed, \( \tilde{\lambda}_\alpha \) is the rescaled variance of the linear combination of the volatility-normalized returns \( \tilde{r}_i \) (given by the eigenvector \( \tilde{V}_\alpha \)), each of which is decorrelated from other such combinations. By construction, the variance \( \tilde{\lambda}_\alpha \) is normalized, which facilitates the comparison of different factors and different markets. We emphasize that diagonalizations of the covariance and correlation matrices are generally not equivalent; in particular, the eigenvalues \( \lambda_\alpha, \tilde{\lambda}_\alpha \) and the eigenvectors \( V_\alpha, \tilde{V}_\alpha \) are different (though in our case, their interpretations should be close). We choose the second option (i.e., Eq. (6)), which inherently reduces stock heterogeneity and heteroskedasticity due to rescaling.

Unfortunately, a straightforward diagonalization of the empirical covariance or correlation
matrix estimated from stock price series is known to be very sensitive to noise (Laloux et al., 1999; Plerou et al., 1999, 2002; Potters et al., 2005; Wang et al., 2011; Allez and Bouchaud, 2012). In particular, only a few eigenvectors corresponding to the largest eigenvalues can be estimated, as illustrated and further discussed in Sec. V.D. As a consequence, conventional diagonalization does not appear suitable for building various representative factors.

B. Our methodology: Indicator-based factors

We propose a different approach to building factors. We begin from the available economic and financial indicators regarding the traded companies, such as their capitalization, sales-to-market, dividend yields, etc. We expect that companies with comparable indicators – at least those with comparable indicators in the extreme quantiles of the indicator distribution – will exhibit correlations in their stock performance. This hypothesis allows us to construct and then test indicator-based factors beyond sectors. To minimize sectorial correlations, we split the stocks into six supersectors of similar sizes, as detailed in Appendix A. The following construction is performed separately for each supersector and then the data are aggregated (see below).

We consider ten indicator-based factors:

1. The dividend factor, which is based on the dividend yield.
2. The capitalization (or size) factor, which is based on capitalization.
3. The liquidity factor, which is based on the ratio of the weekly exponential moving average to the total number of shares (i.e., capitalization/close price).
4. The momentum factor, which is based on the 3-year exponential moving average of past daily returns.
5. The low-volatility (or beta) factor, which is based on the sensitivity to the stock index.
6. The leverage factor, which is based on the debt-to-book value ratio.
7. The sales-to-market factor, which is based on the ratio of sales to market value at the end of the fiscal period.
8. The book-to-market factor, which is based on the ratio of the book value to the market value at the end of the fiscal period.
9. The remuneration factor, which is based on salaries and benefits expense per employee.
10. The cash factor, which is based on the ratio between the free cash flow and the latest market value.

We believe that considering these 10 factors is sufficient and including additional factors will not significantly change our results. In particular we might have included the investment and profitability factors following Fama and French (2015), but we expect that our 10 factors...
already capture the common risk from these two factors. Indeed, sales and cash should be correlated with profitability, whereas the dividend yield and leverage ratio should be correlated with investment.

For each trading day, the stocks of the chosen supersector are sorted according to the indicator (e.g., remuneration) available the day before (we use the publication date and not the valuation date). The related indicator-based factor is formed by buying the first $qn_s$ stocks in the sorted list and shorting the last $qn_s$ stocks, where $n_s$ is the number of stocks in the considered supersector, and $0 < q < \frac{1}{2}$ is a chosen quantile level. The other stocks (with intermediate indicator values) are not included (weighted by 0). In the simplest setting, one can choose equal weights:

$$w_i = \begin{cases} +1, & \text{if } i \text{ belongs to the first } qn_s \text{ stocks in the sorted list,} \\ -1, & \text{if } i \text{ belongs to the last } qn_s \text{ stocks in the sorted list,} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

In attempting to reduce the specific risk, the common practice suggests to invest inversely proportional to the stock’s volatility $\sigma_i$, i.e., to set $w_i = \pm 1/\sigma_i$ or 0. Moreover, the inverse stock volatility should also be bounded to reduce the impact of extreme specific risk. Each trading day, we recompute the weight $w_i$ as follows

$$w_i = \begin{cases} +\mu_+ \min\{1, \sigma_{\text{mean}}/\sigma_i\}, & \text{if } i \text{ belongs to the first } qn_s \text{ stocks in the sorted list,} \\ -\mu_- \min\{1, \sigma_{\text{mean}}/\sigma_i\}, & \text{if } i \text{ belongs to the last } qn_s \text{ stocks in the sorted list,} \\ 0, & \text{otherwise,} \end{cases} \quad (8)$$

where $\sigma_{\text{mean}} = \frac{1}{n_s} (\sigma_1 + \ldots + \sigma_{n_s})$ is the mean estimated volatility over the supersector. In this manner, the weights of low-volatility stocks are reduced to avoid strongly unbalanced portfolios concentrated in such stocks. The two common multipliers, $\mu_\pm$, are used to ensure the beta market neutral condition:

$$\sum_{i=1}^{n_s} \beta_i w_i = 0, \quad (9)$$

where $\beta_i$ is the sensitivity of stock $i$ to the market (obtained by a linear regression of the normalized stock and index returns based on the reactive volatility model \cite{Valeyre et al. 2013}; note that the use of standard daily returns leads to similar results, see Appendix B). If the aggregated sensitivity of the long part of the portfolio to the market is higher than that of the short part of the portfolio, its weight is reduced by the common multiplier $\mu_+ < \frac{1}{2qn_s}$, which is obtained from Eq. (9) by setting $\mu_- = \frac{1}{2qn_s}$ (which implies that the
sum of absolute weights $|w_i|$ does not exceed 1). In the opposite situation (when the short part of the portfolio has a higher aggregated beta), one sets $\mu_+ = \frac{1}{2q_{ns}}$ and determines the reducing multiplier $\mu_- < \frac{1}{2q_{ns}}$ from Eq. 9. This method of ensuring the market neutral condition is better than leaving the residual beta (as in the FF approach) or withdrawing it by subtracting an appropriate constant from all weights. Indeed, under our approach, the factor is maintained to be invested only in stocks that are sensitive to this factor. In turn, subtracting a constant would affect all stocks, even those that were “excluded” and whose weights were set to 0 in Eq. 8. We also emphasize the difference with the conventional FF approach: our factors are built to be market-neutral under Eq. 9, whereas the FF portfolio is built to be delta-neutral (i.e., to have zero net investment):

$$\sum_{i=1}^{n_s} w_i = 0.$$  \hspace{1cm} (10)

The resulting factor is obtained by aggregating the weights constructed for each super-sector. This construction is repeated for each of the ten factors listed above. We emphasize that the factors are constructed on a daily basis, i.e., the weights are re-evaluated daily based on updated indicators. However, most indicators do not change frequently so that the transaction costs related to changing the factors are not significant.

The above procedure can be extended to construct factors from other quantiles, in addition to the first and the last. In this manner, we will consider three portfolios for each factor:

- Q1: long positions for stocks whose indicator belongs to the first 15% quantile and short positions for stocks in the last 15% quantile, as discussed above (for $q = 0.15$).
- Q2: long positions for stocks in the second 15% quantile and short positions for stocks in the next-to-last 15% quantile (i.e., positive weights are assigned to stocks ranging between $0.15n_s$ and $0.30n_s$ in the list, and negative weights are assigned to stocks ranging between $0.70n_s$ and $0.85n_s$).
- Q3: long positions for stocks in the third 15% quantile ($0.30n_s - 0.45n_s$) and short positions for stocks in the third-to-last 15% quantile ($0.55n_s - 0.70n_s$).

To evaluate common risk with each factor, we introduce the factor correlation level (FCL) as the square root of the ratio between the empirical variance of the indicator-based factor and the total empirical variance of the constituent stocks:

$$FCL(t) = \left( \frac{\text{EMA} \left\{ r_{\pi}^2(t) \right\}}{\text{EMA} \left\{ \sum_{i=1}^{n} w_i^2(t)\sigma_i^2(t) \right\}} \right)^{1/2},$$  \hspace{1cm} (11)
where \( r_\pi(t) \) is the daily return of the factor,

\[
r_\pi(t) = \sum_{i=1}^{n} w_i(t) r_i(t),
\]

(12)

where \( w_i(t) \) is the weight of the stock \( i \) in the factor, and \( \sigma_i(t) \) is the volatility of the stock \( i \) estimated using the reactive volatility model \( \text{[Valeyre et al., 2013]} \). The exponential moving average (EMA) is used with a long averaging period of 200 days to reduce noise by smoothing measurements. We emphasize that the above sum aggregates stocks from all supersectors. We also considered the standard volatility estimator based on a 40-days exponential moving average and obtained similar results (see Appendix B). The square root in Eq. (11) is taken to operate with volatilities instead of variances. The estimator (11) is built analogously to Eq. (6) for the eigenvalues \( \tilde{\lambda}_\alpha \) of the correlation matrix. This analogy relies on the assumption that the indicator-based weights \( w_i \) are close to an eigenvector of the correlation matrix. Since the true correlation matrix is unavailable, it is impossible to directly validate this strong assumption. We will therefore resort to indirect validations based on empirical correlations of the constructed factors and on the profitability of trading strategies derived from such factors. Note also that the weights \( w_i \) depend on the choice of the quantile \( q \), such that we expect to have slightly different results for different quantiles (see Fig. 4 below). Simultaneously, the analogy to eigenvalues of the correlation matrix allows various factors to be classified according to their “importance”: larger values of FCL mean stronger volatility of the factor and therefore higher common risks. For example, when the correlation of small capitalization firms increases while the volatility of individuals stocks remains stable, the FCL of the capitalization factor will increase, and the volatility of the factor will increase. In general, the risk of a factor is proportional to the average individual volatility multiplied by the FCL. For this reason, FCL can be interpreted as an average correlation measure between stocks within the factor that is also directly linked to the common risk level underpinning the factor. It must also be emphasized that the FCL estimator is dynamic, i.e., it can capture changes in the correlation structure of the market over time.

IV. Data

In this study, we use only liquid stocks (most with capitalization greater than 800 million euros), thus excluding microcap firms that are typically the main focus of the labor studies we have cited. Thanks to the European accounting regulations, the remuneration must be provided by European companies on a regular basis and can thus be accessed through
### Table I

<table>
<thead>
<tr>
<th>Region</th>
<th>Capitalization (B€)</th>
<th>Number of employees (thousand)</th>
<th>Remuneration (M€)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Europe</td>
<td>$(13 \pm 25)$</td>
<td>$(41 \pm 78)$</td>
<td>$(0.13 \pm 0.99)$</td>
</tr>
<tr>
<td>U.K.</td>
<td>$(11 \pm 21)$</td>
<td>$(38 \pm 87)$</td>
<td>$(0.08 \pm 0.08)$</td>
</tr>
</tbody>
</table>

Basic statistics (mean and standard deviation) regarding capitalization (in billions of euro/pounds), number of employees (in thousands), and remuneration (in millions of euro/pounds) from the FACTSET database. Since minimal capitalization is approximately 800 million euros, the distribution is truncated at small capitalizations.

commercial databases such as FACTSET. Lacking such information for the U.S. market, we mainly focus on the European companies. To reveal possible nation-specific features, the analysis is performed for two trading universes: (i) the 569 biggest companies in Europe (London Stock Exchange, Euronext, Eurex, SIX), and (ii) the 258 biggest companies on the London Stock Exchange only. Although the twice-as-large European universe is expected to increase the statistical significance of the results, the consideration of the U.K.-bounded universe allows us to eliminate country biases and additional fluctuations (e.g., due to currency exchange rate variations). We will show that the major conclusions are similar for both universes. In addition, we will validate our indicator-based methodology on the U.S. universe that includes the 569 randomly selected companies whose capitalization is above 1 billion of dollar. Note that the universe of the 1229 biggest firms in the U.S. studied by Fama and French (2008) is comparable to our European universe in terms of capitalization and liquidity.

All the companies that we include in the European and U.K. universes belong to the small (below 1 billion euros), mid (between 1 and 5 billion euros), large (between 5 and 20 billion euros), or big (above 20 billion euros) capitalization categories. The data set consists of 3612 daily single stock close prices from January 2001 to July 2015. **Note that most Fama and French data begin from 1963, which leads to greater t-statistics.** We rely on daily prices (instead of the monthly prices that are commonly used in the literature) to have more precision in the temporal granularity of our FCL estimation. In addition, several economic and financial indicators are extracted from the FACTSET database: book-to-market, capitalization, sales-to-market, dividend yield, debt-to-book, free cash flow, salaries and benefit expenses, and the number of employees on an annual basis (see Table I). For the European universe, we partly offset geographical biases in each indicator by renormalizing it to its median in the country. For instance, remuneration is divided by its median by country, whereas the median by country is subtracted from the moving average of returns in the case of momentum.
V. Empirical results

In this section, we present the main results of our methodology applied to the European, the U.K. and the U.S. universes. We mainly focus on the remuneration indicator, which has largely been ignored so far. We will show that remuneration yields a non-negligible common risk and represents a small anomaly. The possibility of revealing the role of the remuneration factor relies on the proposed FCL methodology.

A. Correlation between remuneration and capitalization

First, we inspect the empirical joint distribution of remuneration and capitalization. This inspection is important because a positive size-wage effect has already been well documented in the economic literature for microcapitalization firms (Lallemand et al., 2007). The wage gap due to firm size is approximately 35% (Oi and Idson, 1999) because large firms (but remaining in the microcapitalization category) demand a higher quality of labor and set a higher performance standard that must be supported by a compensating wage difference. Note that the magnitude and determinants of the employer-size wage premium vary across industrialized countries. Indeed, individual effects explain approximately 90% of inter-industry and firm-size wage differences in France (Abowd et al., 1999), while almost 50% of the firm-size wage differentials in Switzerland derive from a firm-size effect (Winter-Ebmer et al., 1999). In the U.K., larger firms pay better because of internal labor markets that reward effort and firm-specific capital (Belfield et al., 2004). A visual inspection of Figure 1 (top) suggests that there is almost no correlation between remuneration and capitalization within the class of liquid stocks (that excludes microcapitalization firms) and, in any case, residual correlation is not significant. As a consequence, a larger firm from our sample does not necessarily pay its employees more. This result is consistent with the literature.

To confirm that the remuneration anomaly exists for different capitalizations, we split our sample in two groups: the above-median group of stocks whose capitalization exceeds the median size of our sample, and the below-median group with the remaining stocks (we recall that both groups exclude microcapitalization firms). For each group, we build its own remuneration factor. Figure 2 shows that the cumulative performances of both remuneration factors are statistically different from 0 and behave similarly. An apparent slight outperformance of the factor constructed for the below-median group is not significant and can be attributed to statistical fluctuations.

Further investigations on the size-wage effect compel us to explore this relation per employee. Figure 1 (bottom) reveals that remuneration is positively correlated to capitalization per employee, i.e., remuneration increases with the amount of capitalization.
Figure 1. Remuneration versus capitalization (top) and remuneration versus capitalization per employee (bottom). Full circles and empty diamonds present large U.K. and European companies, respectively. Both quantities are shown in local currency and plotted on a logarithmic scale to account for significant dispersion in capitalization and remuneration. Solid and dashed lines indicate the linear regression between the logarithms of these quantities for the U.K. and European universes, respectively (the respective slopes are 0.34 and 0.30, and $R^2$ goodness of fit are 0.48 and 0.58, respectively). Since the records on remuneration and capitalization of each company in the FACTSET database are updated at different moments of the year, data were averaged over the period from 15/12/2014 to 30/07/2015. Similar results were obtained by taking the latest record for each company (not shown). Two subplots show the empirical distributions of capitalization (top) and remuneration (right) among the biggest European companies.
Figure 2. Similar cumulative performance anomalies of two remuneration factors for quantile Q1: one is constructed from stocks whose capitalization exceeds the median size of our sample, and the other is constructed from the remaining stocks. The cumulative performance of both factors after 15 years is approximately 9%, yielding an annualized performance of 0.6% (compared with 0.68% in Table IV). These curves are obtained for the European universe (the results for the U.K. universe are similar and thus not shown). The annualized performance for the remuneration factor is thus biased and cannot be fully explained by an unbiased random walk.
per employee. One plausible explanation for this phenomenon might be that reducing the number of employees (in particular, underperforming employees) increases marginal remuneration. In summary, there is no correlation between capitalization and remuneration for both universes of firms with capitalization over 800 million euros. Simultaneously, remuneration increases with the amount of capitalization per employee – as if the cake had to be shared fewer times.

B. Remuneration as a common risk

The motivation for building indicator-based factors relies on the hypothesis that the stocks with close indicator values behave similarly and thus share common risks. To verify this hypothesis, we compare three realizations of the remuneration factor built on different quantiles (Q1, Q2, and Q3), as described in Section III.B. Figure 3 shows weak but highly significant correlation between the daily returns of the remuneration factors from quantiles Q1 and Q2 (top) and Q1 and Q3 (bottom), notwithstanding that these factors have no stocks in common, which is the indirect proof that the companies adopting similar remuneration policies (e.g., paying their employees well) share a common risk. The weak correlation can be explained by a rapid decrease of the stock sensitivity to the remuneration factor with the quantile: the correlation level of (Q1, Q3) is measured to be half that of (Q1, Q2). The common risk is of the same order of magnitude as the residual risk, even for Q1. In summary, only the stocks in the extreme quantiles are the most sensitive to the remuneration factor. This observation is also confirmed by the anomalies that are more important for extreme quantiles, as shown in Figure 4.

C. Factor correlation level as a proxy of the eigenvalues

Ordering the factors based on their importance is central for the asset pricing analysis. As discussed in Sec. III.B the relevance of indicator-based factors can be characterized using the factor correlation level (FCL) defined by Eq. (11). If the factor weights were approximately proportional to the elements of an eigenvector of the correlation matrix, the FCL would be an estimator of the volatility of this factor. The factors with larger FCL would most likely have greater impact on the portfolio returns for the same exposure. In general, the risk of a factor is proportional to the average individual volatility multiplied by the FCL. Thus, FCL can be interpreted as an average correlation measurement between stocks within the factor.

Using the daily returns of each factor and estimating the realized volatility of each stock, we compute the FCL for each factor based on Eq. (11). Figure 5 shows the time evolution
Figure 3. (Top) Correlation between the daily returns of the two remuneration factors constructed on quantiles Q1 (0%-15% and 85%-100%) and Q2 (15%-30% and 70%-85%), which have no stocks in common. The daily returns of these factors are weakly correlated but correlation is significant: the slope and its 95%-confidence interval is 0.19 ± 0.03. (Bottom) For comparison, the correlation between the daily returns of the remuneration factors Q1 and Q3 (30%-45% and 55%-70%) is shown, with the slope and its 95%-confidence interval 0.10 ± 0.03. Both graphs were obtained for the European universe. Similar graphs for the U.K. universe yield the slopes 0.23 ± 0.03 and 0.02 ± 0.03 for Q1-Q2 and Q1-Q3 correlations, respectively (graphs are not shown but are available upon request).
Figure 4. The cumulative performance of the remuneration factor for the three quantiles (Q1, Q2 and Q3) for the European universe (the graph for the U.K. universe is similar and is available upon request). Biases are more pronounced for Q1 than for Q2 or Q3, which might be explained by the possibility that stocks belonging to the extreme quantile are the most sensitive to the remuneration anomaly.

of the FCLs for ten indicator-based factors defined in Sec. III.B. For comparison, we plot the FCLs for the European and the U.S. universes (the FCLs for the U.K. universe behave similarly and are thus not shown). First, the FCLs exhibit strong variations over time. In particular, the FCLs of two factors can cross each other, i.e., the ordering of the factors based on their “importance” can evolve over time. For both universes, the low-volatility factor appears as the most important, followed by capitalization and momentum factors. Other factors are smaller but statistically significant. Averaging the FCL over 15 years allows us to order the factors according to their importance. Table II suggests the following order for the European universe: low-volatility (1.73), capitalization (1.72), momentum (1.41), sales-to-market (1.22), liquidity (1.19), book-to-market (1.13), dividend (1.09), leverage (1.07), remuneration (0.99), and cash (0.92). All these FCLs are higher than the noise level of 0.78 that we estimated by building a “noise factor” according to an arbitrary non-financial indicator, such as an alphabetic order. Even though the remuneration factor is relatively small, its magnitude remains statistically relevant in comparison with other well-known factors. For example, the FCLs of the book-to-market, dividend, leverage and cash factors are close to that of the remuneration factor. Their low values mean that these factors are not particularly volatile and that the related common risks are low. Conversely, the low-volatility factor (excluded from the FF approach) has the
### Table II

The mean value of the FCL for ten factors (quantile Q1) averaged over the period from 10/08/2001 to 31/07/2015, for the European, U.K., and U.S. universes. According to these values, the main factors for asset pricing are the low-volatility factor (excluded from the FF approach), followed by the capitalization, and momentum factors. We see that the book-to-market and remuneration factors are of the same order of magnitude such that the remuneration factor should have the same importance in asset pricing models as the book-to-market factor. We also estimated the FCL of the market (last column). The FCL of a noise factor was estimated to be around 0.8 for three universes implying that all presented factors exceed noise. Note that we could not construct the remuneration factor for the U.S. universe because of lack of systematic remuneration data for U.S. companies.

The highest FCL and is thus identified as the first potential source of risk in a portfolio, after market index and sectorial risks. Notably, the low-volatility factor is comparable to the capitalization factor and greatly exceeds the book-to-market factor, the two “major” factors identified in the Fama and French (1993) model.

### D. Comparison with the principal component analysis

The principal component analysis (PCA), which is applied to decorrelate time series, consists in forming the empirical correlation matrix from daily stock returns and then finding its eigenvalues and eigenvectors. In practice, the number of stocks in a traded universe (typically 500 - 1000) is often comparable to the number of available historic returns per stock (for instance, 3612 daily returns in our dataset), that makes this general method strongly sensible to noise, as discussed in Laloux et al. (1999; Plerou et al. 1999, 2002; Potters et al. 2005; Wang et al. 2011; Allez and Bouchaud 2012).

In order to illustrate this limitation, we apply the PCA to the European universe and compute numerically 569 eigenvalues. Figure [Fig] shows the histogram of square roots of the obtained eigenvalues, i.e., how many eigenvalues are contained in successive bins of size 0.0626. The largest value, $\lambda_{\text{market}}^{1/2} \approx 12.62$, corresponding to the market mode, was excluded from the plot for a better visualization of other values. One can identify approximately ten well-separated single eigenvalues that are typically attributed to market sectors. In turn, the remaining part of (smaller) eigenvalues lying close to each other and thus almost indistinguishable, can be rationalized by using the random matrix theory (Laloux et al. 1999). If the daily stock returns were distributed as independent Gaussian variables (with
Figure 5. Evolution of the factor correlation level (FCL) for ten factors (quantile Q1): the European (top) and USA (bottom) universes (the behavior for the U.K. universe is similar and available upon request). In our interpretation, FCL is a measure of “importance” of factors in asset pricing models. Thick lines highlight the three major factors: low-volatility, capitalization, and momentum. The mean FCLs averaged over 14 years are summarized in Table III. All FCLs are highly volatile, but this volatility is not linked to stock market volatility. In addition, we can see the jump- and cross-over of FCLs. During the 2007–2008 financial crisis, several FCLs collapse for the U.S. universe. Note that we could not construct the remuneration factor for the U.S. universe because of lack of systematic remuneration data for U.S. companies.
mean zero and variance one), the eigenvalues of the underlying empirical correlation matrix would asymptotically be distributed according to the Marcenko-Pastur density

$$\rho(\lambda) = \frac{\sqrt{4q\lambda - (\lambda + q - 1)^2}}{2\pi q\lambda}, \quad (13)$$

where \( q = N/T \) is the ratio between the number of stocks, \( N \), and the number of daily returns per stock, \( T \). These eigenvalues lie between two critical values, \( \lambda_{\text{min}} = (1 - \sqrt{q})^2 \) and \( \lambda_{\text{max}} = (1 + \sqrt{q})^2 \). As a consequence, the eigenvalues obtained by diagonalizing the empirical correlation matrix and lying below \( \lambda_{\text{max}} \) can be understood as statistical uncertainty of the PCA. In other words, the PCA cannot reliably identify the factors with \( \lambda < \lambda_{\text{max}} \). For our European universe, \( q = 569/3612 \) so that \( \sqrt{\lambda_{\text{max}}} \approx 1.4 \) determines a theoretical threshold between larger, significant eigenvalues, and smaller, noisy ones.

Comparing large values in Fig. 6 to the FCL from Table II, we conclude that PCA might identify three major factors: low-volatility (1.73), capitalization (1.72), and momentum (1.41). In turn, the other factors whose the FCL is smaller than the PCA threshold 1.4, would thus be understood as statistical uncertainty in the PCA method. The crucial advantage of our method, in which factors are built from firm-based indicators while market and sectorial correlations are eliminated by construction, is the possibility to go beyond this PCA limit and to identify the factors with smaller FCLs. Moreover, this identification can be performed over time.

### E. Net investment as a proxy of the exposure to the low-volatility factor

Building market-neutral portfolios requires nonzero net investment when the portfolio is exposed to the low volatility anomaly. This anomaly is governed by the low-volatility factor, which is the most influential factor (after market and sectors) according to our FCL measurement (Table III), and unfortunately a residual exposure to the low-volatility factor cannot be easily reduced. As a result, most factors can still be correlated to the low-volatility factor. Thus, when the average beta of long stocks in a factor is significantly different from the average beta of short stocks, the factor is also exposed to the low-volatility factor with a nonzero net investment. The net investment is defined as the difference between long \( (\omega_i > 0) \) and short \( (\omega_i < 0) \) investments normalized by total investment, i.e.,

$$\Delta = \frac{\sum_{i=1}^{n} w_i}{\sum_{i=1}^{n} |w_i|}. \quad (14)$$

By construction, \( \Delta \) can vary between \(-1\) and \(1\) or, equivalently, between \(-100\%\) and \(100\\%\).
Figure 6. Histogram of square roots of eigenvalues, $\lambda^{1/2}$, of the empirical correlation matrix obtained from daily returns of 569 stocks in the Europe universe over the period from 10/08/2001 to 31/07/2015. The largest value, $\lambda_{\text{market}}^{1/2} \approx 12.62$, corresponding to the market mode, was excluded from the plot for a better visualization of other values.

Replacing the individual sensitivities $\beta_i$ in the market neutral relation (9) by the averages $\langle \beta_L \rangle$ and $\langle \beta_S \rangle$ for long and short stocks, the net investment $\Delta$ from Eq. (14) can also be expressed as

$$\Delta = \frac{\langle \beta_S \rangle - \langle \beta_L \rangle}{\langle \beta_S \rangle + \langle \beta_L \rangle}. \tag{15}$$

When the average sensitivities for long and short stocks are similar, net investment is close to 0. In turn, a net bias in $\Delta$ occurs when the average beta is different for long and short stocks. $\Delta$ is a proxy of the exposure to the low-volatility factor that is more reactive and more precise than the estimation obtained through the usual regression of returns.

The bias in the long and short betas in Eq. (15) may also be related to the sensitivity to the market (i.e., to the stock index) of a factor built with the FF approach (i.e., neutral in nominal but not in beta):

$$\beta_{FF} = \langle \beta_L \rangle - \langle \beta_S \rangle = -2\langle \beta \rangle \Delta, \tag{16}$$

where $\langle \beta \rangle = \frac{1}{2}(\langle \beta_S \rangle + \langle \beta_L \rangle)$ is the average beta of the universe that we estimated as $\langle \beta \rangle \approx 0.65$ for the period from 2001 to 2015. The net investment $\Delta$ can also be related to the sensitivity of any beta neutral portfolio or factor (both in the FF approach and in our methodology) to the low-volatility factor (the most influential factor, according to the FCL).

Figure 7 shows that the low-volatility factor has the most important short investment
Figure 7. Evolution of the net investment $\Delta$ for five indicator-based factors for the European universe: capitalization, momentum, low-volatility, book-to-market, and remuneration (the results for the U.K. universe are not shown but are available upon request). We recall that $\Delta$ is a proxy of the exposure to the low-volatility factor. The remuneration $\Delta$ is around zero, and the factor therefore has no correlation with the low-volatility factor. Other factors seem to be more exposed to the low-volatility factor.

(negative values of $\Delta$ ranging between $-80\%$ and $-60\%$), although its sensitivity to the market was maintained at 0. Other factors also have a bias in $\Delta$, including the capitalization and the momentum factors, in particular. In the FF approach, these factors would therefore also have a significant sensitivity to the market. In particular, the low-volatility factor built with the FF approach would be strongly correlated to the market. Moreover, $\Delta$ indicates that most factors have a residual correlation with the low-volatility factor that remains uncorrected by our method. Since 2003, the $\Delta$ of the book-to-market factor (one of the major anomalies investigated by Fama and French) has shrunk, and the related book-to-market anomaly has almost disappeared (see Table [V]). Finally, the remuneration factor shows nearly zero net investment, i.e., it remains uncorrelated with the low-volatility factor.

F. Other inter-factor correlations

Correlations between factors matter as long as one needs uncorrelated portfolios for asset pricing purposes. The indicator-based factors were introduced to build as many uncorrelated portfolios as possible. At the same time, such an explicit construction does not guarantee to yield truly uncorrelated combinations, such as the eigenvectors of the covariance (or
correlation) matrix. Moreover, some indicators may capture the same economic or financial features of the company and may thus be correlated; in other words, different factors may approximate the same eigenvector and thus be highly correlated. In particular, adding new indicator-based factors does not necessarily help to capture new features and may thus be redundant. The choice of the ten indicator-based factors studied in this paper is judged as sufficient with respect to the trade-off between capturing information and remaining uncorrelated. Table III presents the correlation coefficients between ten indicator-based factors estimated from their volatility-normalized daily returns. Clearly, many indicator-based factors remain correlated. If the same estimation was applied to ten independent Gaussian vectors of the same length \( m = 3612 \) elements, the standard deviation of the estimated correlation coefficients would be \( 1/\sqrt{m} \approx 0.0166 \). In other words, the presented correlations between the indicator-based factors are highly significant.

The remuneration factor exhibits correlations with some other factors, and the most significant of these include the following: the sales-to-market \((-0.38)\), dividend \((-0.23)\), and momentum \((0.20)\) factors. These correlations can be explained as follows. First, the companies with low sales-to-market ratios have a high margin and thus the ability to pay their employees well (strong negative correlation \(-0.38\)). The direct link between a firm’s margin and wage is well documented in the labor economics literature. More precisely, there is a relation between margin and labor cost. For instance, a study by the European Central Bank (ECB) and the Organization for Economic Co-operation and Development (OECD) reveals that larger firms make more extensive use of margin for labor cost-cutting strategies, i.e., firms choose to reduce benefits as a cost-cutting strategy \[\text{Babecky et al., 2012}\]. In addition, the positive relation between firm size and the use of cost-cutting strategies that is monotonically increasing and highly significant, is uncovered. Second, the companies that pay high dividends to shareholders tend to remunerate their employees less, yielding a negative correlation of \(-0.23\), which is a direct representation of profit-sharing within firms. Indeed, dividend payments are charged on the profits of the business after all salaries and benefits expenses are paid out. Although this result appears intuitive, it remains important as it reveals the level of correlation between both quantities. The labor economics literature and the corporate finance literature are not very well documented on this particular issue. Finally, companies that perform well and show strong momentum can offer higher remuneration to their employees or, alternatively, the higher remuneration stimulates employees to work better and to imbue the company with momentum (positive correlation 0.20). This is a central and very important result of our research because it highlights the positive relation between pay and performance. The rationale behind this result is discussed in Section [VI].
Table III Correlation coefficients between 10 indicator-based factors for the U.K. companies: Dividend (1), capitalization (2), liquidity (3), momentum (4), low-volatility (5), leverage (6), sales-to-market (7), book-to-market (8), remuneration (9), and cash (10). These coefficients were estimated from daily returns of these factors over the period from 23/02/2001 to 27/07/2015. Daily returns of each factor were normalized by their volatility averaged over 20 days to reduce the effects of heteroskedasticity. Similar correlation coefficients were obtained for the European companies (available upon request).

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</thead>
<tbody>
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<td>Div.</td>
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<td>Book.</td>
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<td>0.05</td>
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<tr>
<td>Rem.</td>
<td>-0.23</td>
<td>0.05</td>
<td>-0.06</td>
<td>0.20</td>
<td>-0.03</td>
<td>-0.17</td>
<td>-0.38</td>
<td>-0.13</td>
<td>-0.11</td>
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<tr>
<td>Cash</td>
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<td>-0.01</td>
<td>0.05</td>
<td>-0.04</td>
<td>0.05</td>
<td>-0.02</td>
<td>0.23</td>
<td>0.05</td>
<td>-0.11</td>
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</tbody>
</table>

It is worth emphasizing that these correlations between factors are not static (as presented in Table III by averaging over 15 years) but evolve over time. For example, Fig. 8 shows the evolution of two correlation coefficients between volatility-normalized daily returns of remuneration, low-volatility, and sales-to-market factors. The correlation between the remuneration and low-volatility factors remains close to zero, with eventual deviations beyond the Gaussian significance range (e.g., during the subprime and financial crises in 2007-2009). These two factors can be considered uncorrelated. In turn, the negative correlation between the remuneration and sales-to-market factors always remains beyond the Gaussian significance range.

G. The anomaly of the remuneration factor and its interpretation

Table IV compares the remuneration anomaly with other factors in terms of the annualized bias (the annualized cumulative return between the last and the first observation days), the Sharpe ratio (the annualized bias normalized by annualized volatility), and t-statistics (the Sharpe ratio multiplied by the square root of the total duration in years). In particular, the t-statistic allows one to reject the null hypothesis of no bias at the 90% confidence level. The bias reveals the level of overperformance due to a particular factor. We observe a significant bias for the dominant capitalization and low-volatility factors, which have been
Figure 8. Correlation coefficients between daily returns of the remuneration factor and of the low-volatility factor (solid line) or the sales-to-market factor (dashed line) for the largest U.K. companies. The coefficients were computed over a sliding window of 90 days. Prior to computation, the daily returns were renormalized by their average volatility over the previous 20 days. The mean values over 15 years are $-0.03$ and $-0.38$ (see Table III), respectively. Horizontal dashed lines show the standard deviation, 0.105, of the same estimator applied to two independent Gaussian samples. Similar results were obtained for the European universe (available upon request).
previously documented. The anomaly of the book-to-market factor seems to have disappeared (see Table [V]). In fact, the Sharpe ratio that we estimated to be 0.49 for the period from 1926 to 2008 in the U.S.\(^3\) became much smaller in recent years (and even changed the sign for the European universe, becoming \(-0.08\)). We suspect that this result can be explained by the change in its exposition to the low-volatility factor. The momentum factor has also changed direction.

The remuneration factor appears as the sixth most important anomaly in the U.K. market, and the eighth most important anomaly in the European market. A bias of 1.21% means that companies that pay better should overperform their less paying competitors by \(2 \times 1.21\%\). The prefactor 2 appears if we assume that 50% is invested in high remuneration and 50% in low remuneration (i.e., there is no exposure to the low-volatility factor and volatility is nearly homogeneously distributed). This is one of the most important results in this paper, as it shows that a market neutral investment style arbitrage strategy based on the remuneration anomaly is likely to deliver positive returns.

Next, assuming that the bias in the remuneration factor consists of an intrinsic bias and contributions from biases of other factors due to inter-factor correlations, the relative impacts of these biases can be estimated by multiplying them by the correlation coefficients in the 9th line of Table [III]. These relative impacts are summarized in the last line of Table [IV]. Since most contributions from other factors are negative, it might be surmised that the intrinsic remuneration bias is even higher than 1.21% (estimated to be around 2.85%) but that its value is reduced due to correlations with other factors. If we were able to build a remuneration factor fully decorrelated from other factors, we would have obtained most likely a t-statistic above 3 (around 3.29, see Table [IV]) that fulfills the requirements formulated by [Harvey et al. (2015)]. Note also that there is no selection bias in our study (we have not analyzed all the different possibilities to finally retain the remuneration factor), such that the condition requiring a t-statistic greater than 3 when taking into account the number of possible anomaly candidates is not applicable. In any event, the observed bias of 1.21% cannot simply be explained by the biases of other factors. The Sharpe ratio of 0.37 indicates that a horizon of \(1/0.37 \approx 2.7\) years is required for the anomaly to be captured and to have a positive return with a likelihood of 84%. From an asset management point of view, it suggests the recommended time horizon to take profits based on this market anomaly.

\(^3\)Based on the publicly available data from Fama and French, [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)
The annualized bias (the annualized cumulative return between the last and the first observation days, as a percentage), the Sharpe ratio (annualized bias normalized by annualized volatility), and the t-statistic (the Sharpe ratio multiplied by the square root of the total duration in years, i.e., by $\sqrt{14.5} \approx 3.81$) for the following 10 indicator-based factors (quantile Q1): dividend (1), capitalization (2), liquidity (3), momentum (4), low-volatility (5), leverage (6), sales-to-market (7), book-to-market (8), remuneration (9), and cash (10). These quantities are estimated for the period from January 2001 to July 2015, for the largest European companies (top lines) and for the largest U.K. companies (bottom lines). The last line shows the relative impacts of the biases of various factors on the remuneration bias (1.21) for the U.K. companies. These impacts are obtained by multiplying the biases in the fourth line by the correlation coefficients from the 9th line of Table III. The annualized bias for the remuneration factor in the U.K. universe is 1.21% with a t-statistic of 1.21. Moreover, if we subtract all the impacts from remuneration’s annualized bias, we obtain an intrinsic remuneration bias of 2.85%. Therefore, we would have a t-statistic of approximately $2.85 \times 1.40/1.21 = 3.29$ that would fulfill the requirements formulated by Harvey et al. (2015).
H. The rationale behind the remuneration anomaly

In a survey paper, Yellen (1984) poses the question of why firms do not cut wages in an economy characterized by involuntary unemployment? Indeed, unemployed workers would prefer to work at the real wage rather than being unemployed, but firms will not hire them at a lower wage simply because any reduction in wage would lower employee productivity. This is Yellen’s most-cited paper, and it stipulates that the amount of effort that employees put into their job depends on the difference between the wage they are getting paid and what they perceive as a “fair wage”. The bigger the difference, the less hard they tend to work, which highlights the idea that paying employees more than the market clearing wage may boost productivity and ends up being worthwhile for the employer. Paradoxically, cutting wages may end up raising labor costs since it will negatively affect productivity (Stiglitz, 1981). Hence, productivity is the main argument, which is confirmed by other theoretical papers that consider employees to be more productive in larger firms and thus explain why they demand higher wages (Idson and Oi, 1999). The other arguments are as follows. Given job contract incompleteness, not all duties of an employee can be specified in advance. For this reason, monitoring is a central instrument to control production costs (Alchian and Demsetz, 1972). Unfortunately, monitoring is too costly and sometimes inaccurate due to measurement error. Instead of having costly and imperfect monitoring, firms can offer higher wages to their employees to create an incentive for the employee not to lose their high wage by being fired (Shapiro and Stiglitz, 1984). In this context, paying a wage in excess of the market clearing wage can be seen as an efficient way to prevent employees from shirking. The attractiveness of wages to skillful workers also contributes to reduce their turnover. Moreover, raising wages partly eliminates job demands from less performing candidates who would fear competing with overperforming candidates. This adverse selection is a subtle support for the fair wage hypothesis because paying fair wages will attract only the more skillful workers and deter lemons and will thus help avoid costly monitoring devices in the recruitment processes. In summary, the motivation for the fair wage-effort hypothesis is a simple observation of human nature arguing that employees who receive less than what they perceive to be a fair wage will not work as hard as a consequence. In the very same vein, Akerlof and Yellen (1990) set up a model of unemployment in which “people work less hard if they are paid less than they deserve, but not harder if they receive more than they deserve”. The model puts in equation the fair wage-effort hypothesis to represent the idea that a poorly paid employee may be keen on taking its revenge on its employer.
VI. Discussion

A. Fama and French approach

Fama and French (1993, 2015) use time series of 25 portfolios, each portfolio built with similar capitalization and book-to-market stocks. They regress the monthly performance $R_i(t)$ of each portfolio $i$ on the returns $f_j(t)$ of different factors $j$:

$$R_i(t) = a_i + \sum_j b_{i,j} f_j(t) + \varepsilon_i(t),$$

where $a_i$ and $\varepsilon_i(t)$ are portfolio-specific intercept and noise, and $b_{i,j}$ is the estimated sensitivity of the $i$-th portfolio to the $j$-th factor.

If the remuneration factor had to be investigated using the FF approach, how could one proceed? Five different portfolios might be built with stocks sorted according to remuneration and then at least three major factors might be used: the market index, capitalization, and book-to-market factors (the factor returns, $f_j(t)$, would be estimated through the performance of the long-short portfolio, e.g., buying the high capitalization and shorting the low capitalization, or buying the high book-to-market and shorting the low book-to-market). The intercept, $a_i$, for the 5 different portfolios might be measured with their t-statistics to assess whether the remuneration is an anomaly. One might also measure the $a_{\text{high}} - a_{\text{low}}$ and its t-statistics, as in Table 2 by Fama and French (2008). Finally, the remuneration factor might be added to the regression panel and the $R^2$ for every portfolio might be measured to quantify how well the data fit the statistical model and how well the common factors explain the price returns.

Instead, we simply measure the average returns of the HML portfolio (see Table IV) built to be beta-neutral without any regression, as we construct our remuneration factor as uncorrelated to the main factors. That should be close to the $\frac{1}{2}(a_{\text{high}} - a_{\text{low}})$ of the FF approach, or close to the average return of the HML portfolio built to be delta-neutral (see Table I from Fama and French (2015)). This is due to the fact that the remuneration factor is not exposed to the market index, low-volatility and book-to-market factors. However, the FF approach would not account for the fact that remuneration depends on sectors (see Table V). Using the volatility of the portfolio, we can also measure the t-statistics to learn whether the anomaly is statistically significant, and we measure the FCL to quantify how well the common factors explain the price returns.

In Appendix B we compare the FF approach to our methodology. In particular, we show that sectorial constraint and beta-neutral property were the two key advantages of our factors construction: without them, the FF approach applied to the same period,
Table V Sectorial variations of the median of the book-to-market and of the remuneration (in euros) for the U.K. universe in 2014. Both book-to-market value and remuneration vary substantially across different sectors.

would give insignificant results for the remuneration factor (we recall that most Fama and French data begin from 1963, which leads to greater t-statistics).

B. Advantages and limitations of the methodology

Our methodology has several advantages over the FF approach:

1. The estimated FCL quantifying the relevance of the factor does not depend on the number of considered factors, in contrast to the $R^2$ argument of the FF approach (e.g., see Table 6 in Fama and French (1993)). Thus, one can select the most important factors (e.g., stock index, low-volatility, capitalization, liquidity, and momentum factors) in asset pricing models.

2. The sensitivities of the different common risk factors to the market (i.e., to the stock index) are maintained at zero even for the low-volatility factor, which is an important feature because the market mode may have a hundred times greater impact on portfolio returns than other factors.

3. The factors are constructed to be sector neutral, which allows one to better identify their impacts on price variations, which is important because intra-sector correlations are typically more important than within-factor correlations. Notably, the book-to-market factor of FF approach also captures sectorial risk, as the firms are not priced in the same way from one sector to another (see Table V). In particular, the remuneration is very different from one sector to another.

4. Weights ($w_i$) of the stocks that are close in capitalization (or in book-to-market, or in remuneration, etc., depending on the factor) are of the same order of magnitude that
reduces the specific risk of the factor.

5. Maintaining factors beta-neutral at any time reduces the noise of factors, even those that are not supposed to be correlated to the stock index. In fact, we will show in Appendix B that in the case of factors uncorrelated to the stock index, the beta-neutral constraint reduces the volatility of the factor by 1.2% on an annualized basis.

6. Our method enables the inclusion of the low-volatility factor into the cross-section of average returns (in contrast to the FF approach) without any multiregression model. The low-volatility and capitalization factors were found to provide the largest anomaly (see Table IV). In addition, the low-volatility factor was also identified as the major contribution to risk, according to our measurement (see Fig. 5). Surprisingly, the capitalization factor, which had previously been considered as the most important, now occupies the second position. Moreover, the book-to-market factor identified by Fama and French [1993] as important, has eventually become a minor factor (and is just slightly more important than the remuneration factor) after having eliminated the sectoral and market modes.

The main limitations to our methodology are related to the methodology itself. Indeed, although introducing indicator-based factors and their relevance assessments through the FCL were inspired by eigenbasis, this construction does not pretend to yield true eigenvectors and eigenvalues of the covariance (or correlation) matrix. In particular, correlations observed between several factors (e.g., the remuneration and sales-to-market factors) indicate that the decorrelation performed is not perfect. Although the construction of factors can be further refined to make them less correlated (e.g., by splitting the stocks into smaller groups than supersectors), it is difficult to quantitatively assess the quality of such improvements.

VII. Conclusion

We identify a new anomaly in asset pricing that is statistically significant and economically relevant. It is linked to remuneration: the more a company pays for salaries and benefits expenses per employee, the better its stock performs. We show that remuneration is a common risk factor although its magnitude appears relatively small compared with dominant factors such as low-volatility or capitalization. It also appears that only the companies that belong to extreme quantiles are sensitive to the remuneration factor. To validate the abnormal performance associated with the remuneration factor, we check that performance is not explained by other major factors such as low-volatility, capitalization, book-to-market, or momentum. This finding is an empirical contribution to the asset pricing because employee’s remuneration has not been accounted for in so far, while it is a determinant element
in social sciences including labor economics, sociology or management. These various strands of literature show that strong attention should be paid to wages and more generally to labor decisions that are likely to affect firms’ value. The economic interpretation of our key finding is mainly based on a rational explanation of the remuneration anomaly: wages and employee performance are positively correlated. This argument is overall supported by the efficiency wage theory, which claims that rising wages is the best way to increase output per employee because it links pecuniary incentives to employee performance. But it is also supported by several studies highlighting the prominent role of operating leverage as a main source of riskiness of equity returns that is comparable in magnitude to financial leverage.

For this purpose, we introduce an original methodology, coined “Factor Correlation Level” (FCL), to build indicator-based factors. The FCL describes the ability of stocks within the factor to move in a common way and thus reflects the common risk level underpinning each factor. The FCL methodology is a theoretical contribution to the asset pricing literature. Indeed, it allows ordering the factors according to their capacity of taking into account the variability of stocks. This ranking can help fund managers to select the most important factors to set up an asset pricing model and well balanced portfolios. The FCL approach is an alternative to the common practice in asset pricing studies where factor selection depends on several statistical criteria that do not necessarily convey the same information.

Implications of this work are important, numerous and go far beyond asset pricing literature. A first investment style implication of our finding is that the companies that pay better should overperform their competitors by 2.42% per year. In other words, a market neutral investment style arbitrage strategy based on the remuneration anomaly would likely deliver positive returns. A second economics implication is that a company might operate better if it could attract the best human resources while maintaining the company as competitive as possible by keeping only those employees who are productive. While we find that a company that pays too much its shareholders, pays less to its employees according to the negative correlation between remuneration and dividend factors, attention should be brought by top managers to this trade-off between equity capital and labor remuneration. A third research implication is that our new methodology suggests the following ranking for the European stocks according to their respective FCLs: low-volatility (1.73), capitalization (1.72), momentum (1.41), sales-to-market (1.22), liquidity (1.19), book-to-market (1.13), dividend (1.09), leverage (1.07), remuneration (0.99), and cash (0.92). In particular, the low-volatility factor, which is excluded from the FF approach, is the next most important component following the market factor (i.e., the stock index). The remuneration factor is comparable to the book-to-market factor and thus not negligible. We conclude that a five factor model should encapsulate the first five anomalies ordered by their FCL.
Table VI Six supersectors that we used to split stocks and to construct the indicator-based factors (from the FACTSET database). Note that we mixed very different industries to have 6 supersectors with approximately the same number of stocks. Even if different industries were grouped randomly into six supersectors, we show in Appendix B that our methodology would reduce significantly the sectorial risk of different factors.

### Appendix A. Supersectors

Following the Global Industry Classification Standard (GICS), we constructed six supersectors as summarized in Table VI. This redistribution has been performed manually and has aimed at minimizing intrasector correlations and at obtaining an almost equal number of stocks in each supersector. We emphasize that final portfolios include the stocks from all supersectors, i.e., this redistribution is only an intermediate technical step to improve the factors.
Appendix B. Comparison with FF approach

In order to highlight the advantages of our methodology as compared to the standard FF approach, it is instructive to consider incremental transformations from one method to the other. In this way, one can analyze the respective roles of several proposed improvements. For this purpose, we implement the standard FF approach and its progressive modifications.

- **A0 (the standard FF approach):** According to Table I from Fama and French (2015), stocks are subdivided two groups of small (below median) and large (above median) capitalization. Within each of two groups, assets are ordered according to the chosen indicator (e.g., remuneration) and then split into three subgroups (top, medium and bottom 33%). The related portfolio is constructed by buying the top 33% and selling the bottom 33% assets from the sorted list with equal weights. Such prepared two portfolios (for small and large capitalization groups) are then merged into a single FF portfolio. To be comparable with our methodology, the portfolio is rebalanced on daily basis (note that the original FF approach stipulated monthly rebalancing). The constructed portfolio is delta-neutral.

- **A1:** The same rules as A0 except for buying top 15% and selling bottom 15% assets (as in our methodology);

- **A2:** The same rules as A1 except that the splitting into small and large capitalization groups is withdrawn;

- **A3:** The same rules as A2 except that we add sectorial and geographical constraints as in our methodology. In other words, assets are split into 6 supersectors (see Appendix A), the portfolio construction is performed individually for each supersector and then the obtained portfolios are merged. In addition, we normalize the chosen indicator (e.g., remuneration) by the median per country to correct for geographical biases;

- **A4:** The same rules as A3 except that equal weights are replaced by volatility-based weights as in our methodology;

- **A5:** The same rules as A4 except that the volatility-based weights are rescaled by factors $\mu_\pm$ to get beta-neutral portfolios (beta’s are estimated through a standard methodology);

- **A6 (our methodology):** The same rules as A5 except that a standard volatility and beta estimations (by exponential moving averages) are replaced by the reactive volatility model.

Each of these seven approaches (A0, ..., A6) has been applied to both U.K. and European universes. We computed the mean return and volatility of ten factor-based portfolios introduced in this paper. To be closer to the standard Fama and French framework, we present
Table VII Progressive evaluation of factor performances with incremental transition from the FF approach (A0, top) to our methodology (A6, bottom). For each factor, we present mean monthly return (Mean) and volatility (Std), as well as their ratio (t-stat).

As expected, the change of quantiles (passage from the standard A0 approach to A1) almost does not affect the results. Similarly, a standard volatility/beta estimator and the reactive volatility/beta model lead to similar results (passage from A5 to A6). The most significant changes are observed when passing from A2 to A3 and from A4 to A5.

- In the former case, adding the sectorial constraints (see Appendix A) reduces sectorial biases and allows one to better capture the indicator-based factors. To illustrate this point, let us suppose that remuneration is very high in the energy industry and is low (at approximately the same level) in all other industries. If there was no sectorial constraint, the remuneration factor would be long on the energy industry and short in all other industries. In other words, it would be 100% invested in energy, with eventual high risks. In turn, the sectorial constraint reduces this risk by approximately 1/6 because the strong concentration on energy only remains in the 5th supersector while investments in other industries are necessarily imposed for other supersectors. For instance, if the annualized sectorial volatility is

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<tr>
<td>A0</td>
<td>Mean</td>
<td>0.35%</td>
<td>-0.93%</td>
<td>0.30%</td>
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<td>0.68%</td>
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<td>-0.46%</td>
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<tr>
<td></td>
<td>Std</td>
<td>3.20%</td>
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<td>1.99%</td>
</tr>
<tr>
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<td>t-stat</td>
<td>1.46</td>
<td>-22.40</td>
<td>0.83</td>
<td>-1.49</td>
<td>2.32</td>
<td>0.10</td>
<td>-1.97</td>
<td>-1.40</td>
<td>-0.18</td>
</tr>
<tr>
<td>A1</td>
<td>Mean</td>
<td>0.37%</td>
<td>-0.92%</td>
<td>0.34%</td>
<td>-0.79%</td>
<td>0.75%</td>
<td>0.07%</td>
<td>-0.53%</td>
<td>-0.42%</td>
<td>-0.02%</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>3.15%</td>
<td>0.44%</td>
<td>4.81%</td>
<td>5.52%</td>
<td>3.77%</td>
<td>2.80%</td>
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<td>2.00%</td>
<td>1.96%</td>
</tr>
<tr>
<td></td>
<td>t-stat</td>
<td>1.58</td>
<td>-10.82</td>
<td>1.39%</td>
<td>-0.59</td>
<td>-1.09</td>
<td>1.07</td>
<td>-1.20</td>
<td>-1.05</td>
<td>-0.44</td>
</tr>
<tr>
<td>A2</td>
<td>Mean</td>
<td>0.37%</td>
<td>-1.12%</td>
<td>-0.21%</td>
<td>-0.49%</td>
<td>0.31%</td>
<td>-0.23%</td>
<td>-0.49%</td>
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</tr>
<tr>
<td></td>
<td>Std</td>
<td>3.41%</td>
<td>1.39%</td>
<td>4.80%</td>
<td>6.01%</td>
<td>3.85%</td>
<td>2.54%</td>
<td>3.18%</td>
<td>3.47%</td>
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<tr>
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<td>1.45</td>
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<td>2.66</td>
<td>0.32</td>
<td>-2.40</td>
<td>-1.87</td>
<td>-0.12</td>
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<td>Mean</td>
<td>0.41%</td>
<td>-0.96%</td>
<td>-0.19%</td>
<td>-0.61%</td>
<td>0.31%</td>
<td>-0.21%</td>
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<td>1.17%</td>
<td>3.85%</td>
<td>4.99%</td>
<td>3.35%</td>
<td>2.31%</td>
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<td>-0.19%</td>
<td>-0.60%</td>
<td>0.30%</td>
<td>-0.21%</td>
<td>-0.41%</td>
<td>-0.40%</td>
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<tr>
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<td>-1.79</td>
<td>-2.06</td>
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<tr>
<td>A5</td>
<td>Mean</td>
<td>0.41%</td>
<td>-1.16%</td>
<td>-0.86%</td>
<td>-0.11%</td>
<td>-0.34%</td>
<td>-0.46%</td>
<td>-0.34%</td>
<td>-0.08%</td>
<td>0.22%</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>2.09%</td>
<td>1.97%</td>
<td>1.90%</td>
<td>3.34%</td>
<td>2.37%</td>
<td>1.58%</td>
<td>1.95%</td>
<td>1.94%</td>
<td>1.53%</td>
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<td>2.61</td>
<td>-7.88</td>
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<tr>
<td>A6</td>
<td>Mean</td>
<td>0.45%</td>
<td>-1.17%</td>
<td>-0.82%</td>
<td>-0.16%</td>
<td>-0.36%</td>
<td>-0.40%</td>
<td>-0.03%</td>
<td>-0.10%</td>
<td>0.19%</td>
</tr>
<tr>
<td></td>
<td>Std</td>
<td>2.05%</td>
<td>1.91%</td>
<td>1.94%</td>
<td>3.33%</td>
<td>2.44%</td>
<td>1.59%</td>
<td>2.06%</td>
<td>2.00%</td>
<td>1.50%</td>
</tr>
<tr>
<td></td>
<td>t-stat</td>
<td>2.94</td>
<td>-8.19</td>
<td>-5.63</td>
<td>-0.66</td>
<td>-2.00</td>
<td>-3.36</td>
<td>-0.22</td>
<td>-0.66</td>
<td>1.73</td>
</tr>
</tbody>
</table>

results on *monthly* basis, in contrast to the main text, in which daily basis was used. Table VII recapitulates the main findings for the European universe (similar results were obtained for the U.K. universe, available upon request).
12%, such an enforced diversification would reduce it to 2% on an annualized basis.

- In the latter case, we switch from the delta-neutral to beta-neutral portfolios, i.e., we (partly) remove correlations with the stock market index. We evoke two possible origins to rationalize the significant decrease of volatility when passing from A4 to A5. First, if we suppose that stock beta’s follow a distribution with standard deviation $s_{\beta}$, the average aggregated beta of a random delta-neutral factor built with $2 \times 15\% \times 500 = 150$ stocks would be 0, while its standard deviation would be $2s_{\beta}/\sqrt{150} \approx 16% s_{\beta} \approx 6\%$, where we estimated $s_{\beta} \approx 0.37$ from our data. As a consequence, the volatility added by the random exposure to the market index is around $6\% \times \sigma_m \approx 1.2\%$ on an annualized basis, where $\sigma_m \approx 21\%$ is the annualized volatility of the market index. Second, our construction of beta-neutral portfolio reduces their leverage to ensure Eq. (9). Consequently, smaller investments lead to smaller volatility, as compared to the Fama and French construction with a constant investment.

One also observes that volatilities of factors progressively diminish when passing from A0 to A6. This observation indicates that our modifications better withdraw other common risks and manage to concentrate on the risk of interest.

Looking more specifically to the remuneration factor, one can observe a significant increase of t-stat, from $-0.18$ (insignificant) to 1.73 (significant), when passing from the standard FF approach (A0) to our methodology (A6). In other words, implementing the above improvements allowed us to level up the remuneration factor from noise to a small but significant anomaly.

We complete this Appendix by the following general remark. The variability of results presented in Table VII indicates their dependence on a chosen data analysis method and its parameters. The methodology plays therefore the crucial role, especially when dealing with small anomalies such as remuneration. This highlights the advantage of our method that enabled to detect and quantify such small features in the market behavior. At the same time, our methodology remains robust against some changes in construction of factors, such as replacing conventional volatility estimator by reactive volatility model, using volatility renormalized weights, or changing daily to monthly returns.

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