Expanding the Zoo:
The Circularity-Factor

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Abstract

The Circular Economy (CE) is a framework that falls in the vicinity of the environmental, social, and governance (ESG) paradigm. Yet, it relates much more to the notion of a self-sustaining production process, that limits the produce of non-reusable waste and the reliance of non-renewable inputs. As countries all around the world are starting to transition towards greener and more sustainable economies, investors may want to hedge themselves against the risks associated with such a transition. We therefore propose the circularity factor (CF), a hedging portfolio constructed by buying stocks with a high circularity score (CS) and shorting stocks with a low CS. Controlling for firm-size, we find this to be a profitable strategy in the European, but not in the U.S. market. Furthermore, the dynamics of CF are not to be explained by prominent factor models, and CF stands out against the plethora of members of the "factor zoo" to price the cross-section of European stock returns.

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1 Introduction

The world economy is at a cross-roads. Climate change is undoubtedly one of the most pressing issues of our time, calling for an immediate and coordinated response across various sectors of society. In recent years, the potential for environmental and climate hazards posing a risk to the real economy has infiltrated the actions of financial market participants: assets under management of ESG (environmental, social, and governance) funds amounted to 2.74 trillion USD at the end of Q1 2023, down from its peak of nearly 3 trillion USD in Q4 2021, yet up from the merely 1.1 trillion USD in Q2 2020 (Bioy et al., 2023). The rationale behind this is simple, yet profound – climate risk is investment risk. In his 2020 annual letter, BlackRock CEO Larry Fink almost already famously wrote that "our investment conviction is that sustainability- and climate-integrated portfolios can provide better risk-adjusted returns to investors" (Fink, 2020).

Looking further out into the future, the transition towards a "green" economy does not only call for a shift away from fossil fuel towards renewable energy, but necessitates to rethink the whole production process and make it more self-sustainable. In that sense, a sustainable business model is more than just being environmentally conscious or aware that climate change might bear potential transition and physical risks. Especially when seen from the perspective of the life-cycle of a company's output, "sustainability" is much more related to the reusability and recyclability of a company's production process. This is what is subsumed under the notion of the "Circular Economy" (CE), which stands in contrast to the linear economy of produce-consume-throw away. In particular, it is the degree to which a company's production process is integrated into a closed cycle that can refurbish used products as inputs and produce recyclable output , such that the amount of material that leaves such a cycle as waste is minimized. Thus, circularity is a much more refined subcomponent of ESG that puts more emphasis on a sustainable and perpetuating production process.

The question we thus try to answer in this paper, is whether such considerations about the circular economy are priced in the cross-section of stock returns, i.e. whether there exists a hedging portfolio that protects investors from a state in which non-renewable resources are in short supply.

In December 2015, the European Commission adopted the first *Circular Economy Action Plan* (CEAP). The legislative targets in particular the design and consumption of products, such that resources and produces are kept within the EU economy for as long as possible. As part of the European Green Deal, a revised CEAP was adopted in March of 2020. Going forward, firms thus face regulatory, but also market-based pressures to comply with the concept of a circular economy. On the one hand, firms that have to resort to non-renewable input will inevitably face higher input costs as resources approach extinction. On the other hand, firms that produce longer lasting and recyclable output might be rewarded with the ability to charge higher prices. Under these considerations, a more circular firm, i.e. a firm with a higher circularity score (CS), shall be expected to generate higher cash-flows in the future than a firm with a lower CS.

Putting these arguments more formally in the spirit of Fama and French (2015), consider the following pricing formula:

$$PV_{i,t} = \frac{\sum_{\rho=1}^{\infty} E\left(div_{i,t+\rho}\right)}{(1+r_i)^{\rho}} \tag{1}$$

where $PV_{i,t}$ is the market-based present value of company i, $E\left(div_{i,t+\rho}\right)$ are expected future earnings of firm i, and r_i is the corresponding discount rate for firm i.[1] Then assuming that $\text{CS}_i > \text{CS}_j$, our considerations would imply that $\sum_{\rho=1}^{\infty} E\left(div_{i,t+\rho}\right) > \sum_{\rho=1}^{\infty} E\left(div_{j,t+\rho}\right)$. If we were to assume that firm i and j currently trade at the same value ($PV_{i,t} = PV_{j,t}$), this would hence require $r_i > r_j$, which in turn implies higher expected returns for firms with a higher CS.

But does the data support this hypothesis? Answering this question is based on the premise that one can accurately measure whether and to what extent an asset complies with what is deemed *sustainable*, *circular* or *environmentally*, respectively *socially*, responsible. ESG scores, generated by prominent rating agencies and data providers are the go-to source for financial market participants (Berg et al., 2022b). Firm-level disclosures that enter the calculation of these metrics also form the basis of our CS. It is, however, no secret that ESG scores come with caveats. A still young, yet already established literature has studied the pronounced disagreement in ESG scores among data providers (Dimson et al., 2020; Christensen et al., 2021; Berg et al., 2022a,b; Avramov et al., 2022).

Yet, these scores are still the best quantitative approximation of an asset's true ESG compliance, such that within the realm of (Fink, 2020) proposition, Engle et al. (2020) construct a profitable hedge portfolio that shorts stocks with low E-scores and buys stocks with high E-scores. Nevertheless, Berg et al. (2023) make an effort to see through these noisy signals. Consolidating the scores of various rating agencies into a single ESG metric, they find that a portfolio constructed from taking a long position in companies with high ESG scores, and shorting stocks with low ESG scores, generates annualized excess returns ranging from 6% in the U.S. to 9% in Japan. Despite the apparent confirmation of ESG related investing to generate *positive* excess returns, the empirical evidence is inconclusive (Atz et al., 2023). Focusing on carbon emissions, In et al. (2019) find a hedging portfolio – another notion in the literature would be: *factor mimicking portfolio* (Giglio et al., 2021) – constructed by buying carbon-efficient firms and shorting their carbon-inefficient counterparts to deliver abnormal returns of 3.5%-5.4% annualized. Findings in Cheema-Fox et al. (2023) confirm this view, as they find low carbon emission firms to deliver higher expected returns than their high-polluting counterparts. Yet, others find the exact opposite (Bolton and Kacperczyk, 2021; Hsu et al., 2023).

The literature does not dismiss the latter results, provides theoretical evidence for why "brown" firms will actually outperform "green" firms going forward, and rather attributes positive excess returns of "green" firms to be a result of sampling bias. Pastor et al. (2022) argue that the *observed* outperformance of green stocks until the early 2020s is merely a product of an unexpected accumulation of negative climate news shocks over that period and not caused by higher *expected returns*

[1] Said differently, r_i is the expected average return on stock i (Fama and French, 2015).

going forward. This very same argument is also brought forth by Giglio et al. (2021). They warn that in combination with a very short sample period over which ESG investing has played a meaningful role, any interpretation of the sign of such a climate risk premium shall be handled with care.[2]

Our findings speak to those, who see higher expected returns for "greener" firms going forward. We find that a portfolio that buys high CS firms and shorts low CS firms generates a monthly expected excess return between 36 and 51 basis points (BP) – depending on the particular sorting procedure – with an annualized Sharpe Ratio of around 0.75. However, these findings only hold for the European market. We henceforth term this observation the European circularity factor (CF^{EU}). In the U.S. market, the very same strategy generates essentially zero expected excess returns. Depending on the number of sorts, the unconditional expected excess return of CF^{EU} has a *t-statistic* of around 2.20 to 2.40, which would not clear the bar of 3.00 for newly introduced anomalies (Harvey et al., 2015). Yet, we hope to provide convincing arguments that CF is not a data mining phenomenon, but is derived from theoretical asset-pricing considerations, such that 3.00 is not a hard threshold in this case.

Second, prominent factor models such as the Fama and French (2015) five-factor model augmented by the Carhart (1997) momentum factor can explain at most one-third of the variation in CF^{EU}, leaving an α of around 50 BP with a *t-statistic* of around 3.00.

Third, we put CF^{EU} to the test against a myriad of 153 existing anomalies to price the cross-section of stock returns in the European market. Applying the algorithm developed in Feng et al. (2020) that combines the *double selection LASSO* of Belloni et al. (2013) with orthodox Fama and MacBeth (1973) regressions, the CF^{EU} stands out among the other constituents of the factor zoo (Cochrane, 2011).

Lastly, the fact that we only find evidence for the existence of a circularity factor (CF) in the European market and not in U.S. market, tempts us to make a conjecture on the debate as to what extent observed ESG-outperformance (Engle et al., 2020; In et al., 2019; Berg et al., 2023) is just driven by an extraordinarily high amount of negative climate news: if this hypothesis were true, our findings would imply that there were more negative news, respectively concerns, about the finiteness/sustainability of our consumption-driven living standards in Europe than in the U.S. This is hard to believe in a globalized and interconnected world, in which (not only) news spread within the blink of an eye. Yet, we have to admit, that it might rather be the increased awareness of investors, triggered by the adoption of CEAP as early as December 2015, that generated this differential treatment of European firms with respect to their circularity score. This does, however, not negate any of the previously mentioned considerations when it comes to higher expected excess return for "green" firms. It rather tells us, that the act of European regulators demonstrating the willingness to take decisive action towards a more circular economy, made and will have to make investors reconsider companies' ability to comply with such an economic framework. This explanation aligns with the *regime shift*

[2] Berg et al. (2023) mention another issue that may impair the causal interpretation between ESG scores and stock returns: if ESG scores proxy for good management quality, the latter may act as confounder, leading to a spurious causal relationship between ESG scores and excess returns.

risk in terms of environmental regulation as laid out in Hsu et al. (2023).

The remainder of the paper is structured as follows: in section 2 we describe the procedure to calculate a company's CS and provide corresponding summary statistics. In section 3 we describe the factor construction and show results for conditionally sorted portfolios on firm-size and CS. Section 4 follows with results for independent and univariate portfolio sorts, before section 5 puts CF – in particular its European version, CF^{EU} – to the test against the zoo of factors for pricing the cross-section of European stock returns. Section 6 concludes.

2 Measuring a Firm's Circularity

We measure a firm's CS based on the methodology proposed in Zara et al. (2022); Zara and Ramkumar (2022).

The computation of a firm's CS requires information about its commitment to ESG related issues. Prominent data providers, such as Refinitiv, Morningstar, or Sustainalytics, transform such qualitative and non-compulsory disclosure into quantitative metrics. These ESG scores form the basis for deciphering a firm's CS.

As in Zara et al. (2022) we source this information from the Refinitiv ESG Dataset (formerly Thomson Reuters Eikon (TR-E) ASSET4). Obviously, our reliance on these voluntary disclosures comes with caveats that drastically limit our sample size. As the widespread adoption of sustainable investing only dates back a couple of years, firms have just recently been incentivized to disclose ESG related information on a broader scale. This limits our sample size both in the time dimension $t = 1, ..., T$ and in the cross-section N_t. Striking a balance between T and N_t therefore precludes us from going further back in time than 2012. Moreover, despite the asset-pricing literature focusing predominantly on the U.S. stock market, we extend the scope to European companies as well. That is, our sample covers both the U.S. as well as the markets in the EU-15[3] plus Switzerland. Going forward, we occasionally denote these 16 European countries as "EU+".

Here we briefly outline the computation of CS. A more in-depth description can be found in Zara et al. (2022). A key principle of CS is the fact that it is a firm- and industry-specific measure. That is, a company's CS is based on its ranking relative to its industry's peers, where an industry is defined at the ???-digit SIC level. This is an important feature, as not all industries are created equally and allows to set a level-playing-field across industries. Such a procedure is for example also used by Standard & Poor's (Dimson et al., 2020). The computation is based on 140 indicators, grouped into five categories: (i) consumption of resources and waste, (ii) internal policies for resource efficiency, (iii) recovery and supply chain alignment, (iv) product responsibility, and (v) sustainability strategy. within each industry, Zara et al. (2022) apply a category-specific weighting based on the

[3]These are the 15 pre-2004 EU Member States: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

Sustainability Accounting Standards Board (SASB) Materiality Map[4], that measures each category's relevance – *materiality* – for measuring the "Circular Economy" in a given industry.

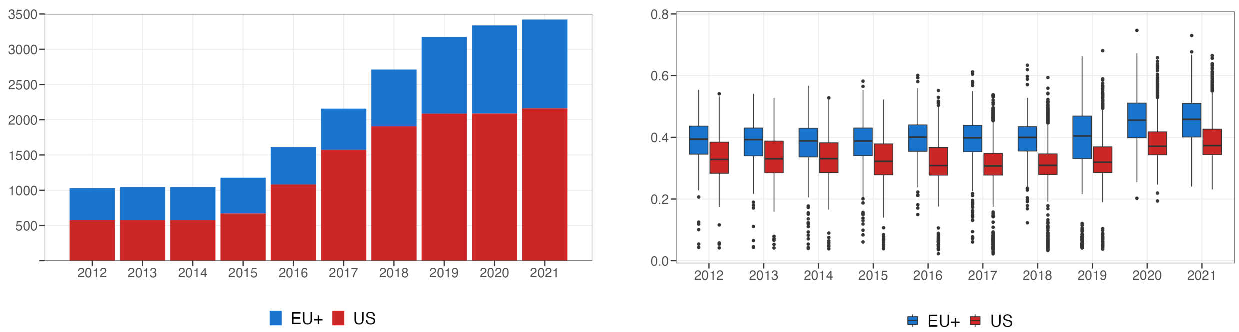
We compute a firm's CS for year t in June of the following year. This accounts for the data providers' publication lag of the underlying metrics. By coincidence, this gap of approximately six months aligns well with the standard practice in the asset-pricing literature, as accounting variables for fiscal year t are assumed to become publicly available in June of $t+1$ (Fama and French, 1992).

Figure 1a shows the number of firms that enter the CS calculations each year over the course of our sample period 2012-2021. Starting out with approximately 1000 companies in 2012, the number of eligible firms rises to almost 3500 in 2021. Yet, the geographic composition stays roughly constant over the sample period, with U.S. companies representing roughly 56% of the total in 2012 and 63% in 2021.

2.1 Circularity Scores across Markets

Figure 1b then shows the corresponding CS distributions for the EU+ and U.S. The horizontal solid black line represents the median, the lower (upper) end of the boxes shows the 25$^{\text{th}}$ (75$^{\text{th}}$) percentile and the whiskers extend to $1.5 \times IQR$ (IQR = Interquartile Range). The median CS in the U.S. is always lower than the one observed in the European market, with the spread widening from 0.066 in 2015 to 0.092 in 2016, but slightly coming down to 0.085 in 2021. Yet, regarding the whole distribution, there is no apparent trending behavior over the course of the sample period. Only in the latter two years do the distributions apparently shift to the right, i.e. towards higher CS. Especially the left tail – circularity scores below 0.2 – is completely deserted.

Figure 1: Circularity Scores Across Regions



(a) Number of Companies

(b) Distribution of Circularity Scores

In Table 1 we dig a bit deeper and break down the CS sample distribution into the 10 industries, represented in our sample. We show sample medians, means, and standard deviations for each industry conditional on the geographic location. Numbers in bold highlight the three industries that

[4]For more information, see: SASB.org.

achieve the highest circularity scores within each region, while the most and least circular industries are colored in green and brown respectively. Apparently, *Renewable Resources & Alternative Energy* is the most circular industry in both markets. Yet, it is *Technology & Communications* in Europe, but *Resource Transformation* in the U.S. that score the lowest in terms of circularity. The between-industry dispersion – measured as the difference between the maximum and minimum CS – is larger among U.S. (0.052 for the median and 0.036 for the mean) than among EU+ (0.042 for the median and 0.034 for the mean) industries. However, the within-industry standard deviation is lower within U.S. industries than within the European counterparts.

Table 1: Circularity Score by Industry and Region

Industry / Region	EU+			US		
	median	mean	std	median	mean	std
Consumer Goods	0.396	0.360	0.132	0.314	0.313	0.081
Extractives & Minerals Processing	0.401	0.373	0.109	0.315	0.313	0.084
Food & Beverage	0.404	0.381	0.114	0.315	0.323	0.085
Health Care	0.383	0.377	0.118	**0.346**	**0.342**	0.062
Infrastructure	**0.421**	**0.386**	0.110	0.325	0.323	0.062
Renewable Resources & Alternative Energy	**0.421**	**0.388**	0.119	**0.359**	**0.347**	0.099
Resource Transformation	0.391	0.369	0.108	0.307	0.311	0.072
Services	0.400	0.367	0.124	0.332	**0.333**	0.064
Technology & Communications	0.379	0.354	0.113	0.328	0.318	0.085
Transportation	**0.410**	**0.386**	0.103	**0.347**	0.327	0.082

Note: Numbers in **bold** mark the three larges circularity scores in each column. Numbers in green highlight the industry with the largest circularity score, and numbers in brown refer to the lowest score respectively. "EU+" refers to the EU-15 countries plus Switzerland.

2.2 Firm Size and Circularity Scores

Besides the well-documented disagreement in ESG scores among rating providers, there is evidence in the literature for larger firms achieving higher scors than their smaller counterparts all else equal (Drempetic et al., 2020; Akgun et al., 2021). This may not come as surprise, as (i) rating agencies might favor larger firms from which they can extract higher fees, or because (ii) larger companies have more resources and capacities to file non-financial and non-mandatory disclosure documents (Hörisch et al., 2015). The following model shall shed some light on whether this is a bias that also CS is plagued by:

$$\log(CS_{i,t}) = \gamma_i + \delta_t + \sum_c \beta_c \log(MC_{i,t})\,\mathbf{1}_{i\in c} + \varepsilon_{i,t}\,, \quad \text{for } c \in \{EU+, US\}\,, \tag{2}$$

where $CS_{i,t}$ is a company's circularity score in year t, $MC_{i,t}$ is a firm's market-capitalization at the time that $CS_{i,t}$ was constructed, and γ_i and δ_t are firm- and year-fixed effects. $\mathbf{1}_{i\in c}$ is an indicator function taking on a value of one, if firm i is places in region c and zero otherwise.

The coefficients of interest $\beta_{EU+} = 0.057$ and $\beta_{US} = 0.068$ are statistically significant at the 1% significance level, revealing the positive relationship between firm size and CS. Said differently, a 1% increase in market-cap will lead to a roughly 0.06% (in the EU+ region), respectively a 0.07% (in the U.S. market) increase in CS. When constructing the circularity factor in the next section, we will take this fact into consideration.

3 The Circularity-Factor

The potential for a size bias in CS will feed into our considerations for constructing the circularity factor (CF) as described below. Nevertheless, we will also provide results for a univariate factor construction in section 4.2. We will first describe the procedure for sorting stocks into portfolios, and then proceed to test whether constructing a hedging portfolio is a profitable strategy – in economic as in statistical terms. Afterwards, spanning regressions serve us to, first, test whether CF is not just a particular construct of already existing prominent factor models, and second, to understand which additional risks our factor might be exposed to.

3.1 Factor Construction

A standard practice in the asset-pricing literature (Fama and French, 1992; Novy-Marx, 2013; Medhat and Schmeling, 2022) is to impose the assumption that accounting variables are published with a lag of about six months. That is, with a company's fiscal year ending in December of year t, the data is treated as becoming publicly available at the end of June of year $t+1$. This convention coincides with the publication lag of the ESG data that underlies our CS construction. Hence, based on information at the end of June in $t+1$, we sort firms into portfolios for the months July $t+1$ until June $t+2$. In June of year $t+2$, new information becomes available and we update our portfolio assignment accordingly, fixing the allocation for the following 12 months starting July $t+2$. Given the tendency of smaller firms to have a lower CS than larger firms, our benchmark procedure constructs double-sorted CS portfolios, conditional on firm size. We value-weight each portfolio and rebalance, i.e. assign portfolio weights, at the end of each month.

When sorting stocks into portfolios along more than one type of characteristic, there are several possibilities one can pursue. In our *conditional* sorts, we first split stocks into two size groups, with the break point being the cross-sectional median of market-capitalization at then end of June in year t. Within these two size groups, we sort stocks according to their CS into $N^{CS} = \{3,4,5\}$ buckets, leaving us with $2 \times N^{CS}$ portfolios. For $N^{CS} = \{4,5\}$, the breakpoints are quartiles and quintiles respectively. For $N^{CS} = 3$, the breakpoints are the 30^{th} and 70^{th} percentile, to which we will loosely refer to as tertiles later on in the text. We also report results for *independently* sorted portfolios. That is, we again split firms into two size groups, however, regardless of a firm's market-capitalization, we also sort stocks into N^{CS} classes based on CS. We then fill our $2 \times N^{CS}$ portfolios with those stocks that lie at the intersection of the two size classes and the N^{CS} CS groups. Given our relatively small sample size compared to other studies in the literature, independent sorts might leave us with sparsely populated sub-portfolios, which may carry over into a poorly diversified factor (see Soebhag et al. (2023) for an excellent review on various portfolio construction procedures). However, the empirical results in section 4.1 will show that despite the apparent size-CS bias showing up in the portfolio sorts, the issue of deserted sub-portfolios is not a concern in our case.

Our benchmark factor will be the conditionally sorted 2×3 long-short portfolio, which we will discuss in more detail in the remainder of the section along with the conditionally sorted 2×4 and 2×5 portfolios. As robustness checks we report results for independent and univariate sorts in section 4.

So far, we have adhered in large part to the extant literature on characteristic-managed portfolios. Now, we will slightly deviate from the standard practice. Most studies take the United States as the market on which to test their factor of interest, and defer the performance in other markets to the robustness checks. Given that measuring a firm's circularity is very much related to the notion of sustainability and ESG, whose institutional frameworks differ vastly across jurisdictions, we will, right away, construct CF for three different geographies: (i) CF^{EU} denotes the circularity factor for the European market, which encompasses the EU-15 countries plus Switzerland, (ii) CF^{US} is built on portfolios comprising only U.S. listed companies, and (iii) CFU denotes the *universal* factor, constructed from merging the European and the U.S. market.

Another deviation from the standard procedure regards the sample period. Our sample does not start before July 2013 and ends in December 2022, leaving us with 114 months of factor returns.

3.2 Factor Exposures and Abnormal Returns

In Table 2 we show average monthly value-weighted portfolio returns for 2×3 sorted CS portfolios conditional on firm size for three different geographic areas. We also report the expected excess return of a long-short portfolio that buys an equally-weighted average of the two CS_{High} portfolios and sells an equally-weighted average of the two CS_{Low} portfolios. Such a strategy turns out to generate an expected excess return, that is statistically significantly different from zero at least at the 5% level, only in the European market. With 36 basis point (BP) per month, the expected excess return is nonetheless sizable.

Yet, when looking across the pod, exploiting such a long-short portfolio does not lead to a profitable investment. The differential between CS_{High} and CS_{Low} is essentially flat. The same holds true when constructing portfolios based on a combined U.S. and European market, suggesting that the U.S. cushions the signal hidden among European companies.

Table 2: Average Monthly Excess Portfolio Returns

	Market: EU-15 + Switzerland			*Market: U.S.*			*Market: EU-15 + Switzerland + U.S.*		
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{Med}	CS_{High}
Small	0.30	0.48	0.79	0.82	0.86	0.89	0.74	0.79	0.78
Big	0.39	0.61	0.62	0.90	0.85	0.83	0.76	0.71	0.75
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A
High - Low	0.36	2.23	0.72	0.01	0.04	0.01	0.01	0.08	0.03

Note: The three panels show average monthly value-weighted excess portfolio returns for the period July 2013 to December 2022. The risk-free rate applied to portfolios in *Market: EU-15 + Switzerland + U.S.*, is the simple average of the European and U.S. risk-free rate.
We construct portfolios based on a conditional 2×3 sort. That is, conditional on a firm's size (small or big, for which the breakpoint is the cross-sectional median in a given year t), we sort firms into three buckets according to their CS, with breakpoints being the 30^{th} and 70^{th} percentile.
$E[r^e]$ denotes the expected excess return of buying the two CS_{High} portfolios and shorting the two corresponding CS_{Low} portfolios. *t-stat* is the corresponding t-statistic and SR^A denotes the annualized Sharpe Ratio.
Numbers are in percent, such that $0.10 \equiv 10$ basis points (BP).

In Table 3 we opt for more granular splits and sort stocks into quartiles and quintiles along the CS dimension – still conditional on size. The previous observations remain unchanged: buying a portfolio, composed of firms with high CS, and shorting a portfolio, composed of firms with low CS, conditional on size, only turns out to be a worthwhile investment in the European market. Compared to the 2×3 sorts in Table 2, the monthly expected excess return increases to 40 BP, and 46 BP respectively, making it an 11%, respectively 28%, increase on a monthly basis vis-à-vis the tertile CS-sorts. Statistical significance also seems to benefit from a more refined differentiation along the CS dimension. In contrast, when incorporating U.S. companies in the portfolio, even the higher degree of granularity does not lead to a long-short strategy that delivers any statistically, nor economically, significant returns.

In sum, a characteristics-managed long-short portfolio, based on a firm's size and circularity score, only turns out to be a devisable strategy that generates returns, which are economically and statistically significantly distinguishable from zero, in the European market. To stress its European descent, we term this strategy the "European Circularity Factor" (CF^{EU}). With monthly expected excess returns ranging from 36 BP for 2×3 sorts, to 40 BP for 2×4 sorts, and 46 BP for 2×5 sorts, this strategy also delivers on a risk-adjusted basis. Annualized Sharpe Ratios (SR^A) for CF^{EU} over the sample period amount to $SR^A_{2\times3} = 0.72$, $SR^A_{2\times4} = 0.78$, and $SR^A_{2\times5} = 0.76$. For comparison, over the same investment horizon, the Euro STOXX 600 generated excess returns of about 29 BP on a monthly basis, with an annualized Sharpe Ratio of $SR^A = 0.24$.

Table 3: Average Monthly Excess Portfolio Returns

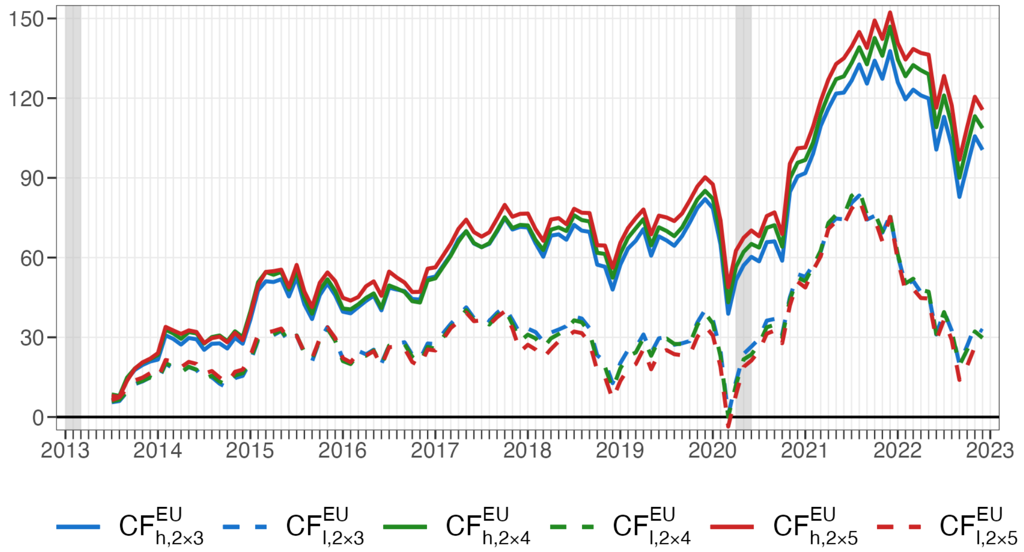
	2×4 Sorts							2×5 Sorts							
	Average Monthly Returns				High-Low			Average Monthly Returns					High-Low		
	Market: EU-15 + Switzerland														
	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	$E[r]$	*t-stat*	SR^A	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}	$E[r]$	*t-stat*	SR^A
Small	0.30	0.47	0.47	0.84	0.40	2.39	0.78	0.31	0.31	0.65	0.51	0.84	0.46	2.35	0.76
Big	0.37	0.63	0.58	0.63				0.30	0.52	0.63	0.54	0.68			
	Market: U.S.														
	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	$E[r]$	*t-stat*	SR^A	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}	$E[r]$	*t-stat*	SR^A
Small	0.86	0.95	0.76	0.89	0.02	0.12	0.04	0.87	0.89	0.76	0.91	0.88	0.03	0.21	0.07
Big	0.82	0.86	0.92	0.83				0.82	0.79	0.95	0.71	0.87			
	Market: EU-15 + Switzerland + U.S.														
	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	$E[r]$	*t-stat*	SR^A	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}	$E[r]$	*t-stat*	SR^A
Small	0.80	0.75	0.76	0.77	-0.01	-0.03	-0.01	0.73	0.76	0.73	0.71	0.77	0.00	-0.01	0.00
Big	0.82	0.79	0.77	0.83				0.83	0.63	0.86	0.68	0.77			

Note: The three panels show average monthly value-weighted excess portfolio returns for the period July 2013 to December 2022. The risk-free rate applied to portfolios in *Market: EU-15 + Switzerland + U.S.*, is the simple average of the European and U.S. risk-free rate.
We construct portfolios based on a conditional 2×4 (on the left), respectively 2×5 (on the right), sorts. That is, conditional on a firm's size (small or big, for which the breakpoint is the cross-sectional median in a given year t), we sort firms into quartiles, respectively quintiles, based on their circularity score.
$E[r^e]$ denotes the expected excess return of buying the two CS_{High} portfolios and shorting the two corresponding CS_{Low} portfolios. *t-stat* is the corresponding t-statistic and SR^A denotes the annualized Sharpe Ratio.
Numbers are in percent, such that $0.10 \equiv 10$ basis points (BP).

Even though all the *t-stat* of CF^{EU} pass the threshold of 2.00, the asset-pricing literature actually deems this number to be too low a bar for declaring statistical significance. For unconditional tests, Harvey et al. (2015) advocate to set the critical value to *t-stat*$=3.00$. Under that convention, none of the circularity factors would be considered a valid anomaly. Yet, Harvey et al. (2015) grant factors some leeway by having to clear a lower threshold in case they are not just a data-mined construct but are derived from or backed by theoretical considerations. We hope our explanations in section 1 can drive home the theoretical underpinnings of CF.

In Figure 2, we plot the historical performance of the two legs of the CF^{EU} for the different $N^{CS}=\{3,4,5\}$ splits. The solid lines represent the long-leg, i.e. the equally-weighted return of the two CS_{High} portfolios, and the dashed lines show the performance of the short-leg of CF^{EU}, i.e. the equally-weighted return of the two CS_{Low} portfolios, on the log scale. The grey areas mark quarters of Euro Area business cycle troughs as determined by the Euro Area Business Cycle Network, which sets the COVID-19 pandemic low for Q2 of 2020. The observed patterns do not come as a surprise to the active market participant: the portfolios tanked during the stock market crash in March 2020, but quickly rebounded in the aftermath as markets got flushed with exorbitant amounts of liquidity, generated by extraordinary monetary and fiscal stimulus. Yet, the bear market of 2022, as Central Banks all around the world embarked on a hawkish path to tame inflation, also left its mark on the $\mathrm{CF}^{\mathrm{EU}}$ portfolios. While the long-legs could slightly recover at the end of the sample and roughly double the initially invested amount, the short-legs retreated to the pre-pandemic average and yield merely a return of around 30% in excess of the risk-free rate.

Figure 2: The Circularity-Factor: Cumulative Excess Returns



Note: For several portfolio sorts – 2×3, 2×4, and 2×5 – we show cumulative excess returns of the long-leg of the European circularity factor ($\mathrm{CF}^{\mathrm{EU}}_{h,*}$) and the corresponding short-leg ($\mathrm{CF}^{\mathrm{EU}}_{l,*}$). The two components are the simple average of the two CS_{High}, respectively two CS_{Low}, portfolios in Tables 2 and 3. Shaded areas mark the quarters of Euro Area business cycle troughs, as dated by the Euro Area Business Cycle Network (€ABCN).

3.3 Spanning Regressions

So far we have established the fact that the European stock market carries some sort of anomaly that we term "Circularity-Factor". We have however not provided any evidence that its dynamics are not just the result of a linear combination of already well-established stock-market, rendering $\mathrm{CF}^{\mathrm{EU}}$ obsolete.

To see whether $\mathrm{CF}^{\mathrm{EU}}$ could just be replicated by a portfolio of prominent factor tilts, we run spanning regressions of the following form:

$$CF_t^{\mathrm{EU}} = \alpha + \mathbf{F}_t\beta' + \varepsilon_t\,, \quad \varepsilon_t \sim N\left(0,\sigma^2\right) \tag{3}$$

where $\mathbf{F}_t$ is a $1\times N^F$ dimensional vector of N^F factors, i.e. returns of a set of characteristically-managed portfolios $\mathbb{F}$, and β is the corresponding $1\times N^F$ dimensional vector of factor loadings. $\mathbf{CF}^{\mathrm{EU}}$ is a $T\times1$ dimensional column-vector of portfolio returns CF_t^{EU}, constituting the circularity factor. Our parameter of interest is α, i.e. that part of $\mathrm{CF}^{\mathrm{EU}}$ that cannot be explained by a portfolio of factors in $\mathbb{F}$. The crucial test that $\mathrm{CF}^{\mathrm{EU}}$ then obviously has to pass, in order to not just be regarded as a particular replication of already well-established anomalies, is whether α is statistically significantly different from zero.

But spanning regressions go beyond just being a device for testing the existential justification of CF^{EU}. They reveal the deeper characteristics of the factor, by unveiling the extent to which it is exposed to various types of risk.

Table 4 presents the results for such spanning regressions where the set of factors, $\mathbb{F}$, constitutes several prominent asset-pricing models: the first column in each panel represents the CAPM (Sharpe, 1964; Lintner, 1965), the second column tests CF against the Fama and French (2015) five-factor model, and the third column adds the Carhart (1997) momentum-factor. In brackets we show the corresponding t-statistic.

Jumping right to the point, the α is statistically significant across all models and portfolio sorts, with the *t-statistic* even ranging in the vicinity of 3.00 for the five- and six-factor model – if one were to transfer the Harvey et al. (2015) threshold from unconditional over to conditional tests. Both these two models can explain about 25% to 30% of the variance in CF^{EU}, yet leaving an expected return between 43.8 BP in Column (2) and 63.5 BP in Column (9) on the table.

As the market-factor has almost no power in explaining CF^{EU} across the board, almost all CAPM-α (Columns 1, 4, 7) are close to their unconditional expected return as reported in Tables 2 and 3. This suggests that CF^{EU} obeys hardly any systematic market movements.

The only factor that CF^{EU} is exposed to in a statistically significant manner, is the size factor (SMB). This may seem intriguing, as by construction, the conditional sorting on size shall control for that very same feature. However, this result suggests that opting for splitting firms into two size groups only might not be enough to rule out the size-bias in CS. Furthermore, while our procedure resorts to the cross-sectional *median* as the breakpoint, SMB for the European market – as retrieved from Kenneth R. French's website – is based on a decile split, denoting the smallest 10% of firms as *small*, and firms in the top decile as *large*. The negative loading thus indicates that our factor still buys rather *large* firms and shorts smaller ones.

The other prominent anomaly that turns out to be occasionally statistically significant is the investment factor (CMA). The positive loading indicates that CF^{EU} captures some patterns that would be generated by buying low-investment companies and shorting high-investment companies. Even though this effect is only statistically significant at the 5% level in one out of six cases, this observation is nonetheless unexpected, as one might have had the strong prior that CF^{EU}, which buys firms with a high CS, would be characterized by companies that invest heavily due to their prescription to sustainability.

Interestingly, the profitability factor (RMW) never turns out to be statistically significant. Our discussion in section 1 about high CS firms generating higher expected cash-flows going forward, might have left the perception that RMW explains a major part of CF^{EU}. Instead, it does not seem to do so.

Table 4: Spanning Regressions

	$CF^{EU}_{2\times3}$			$CF^{EU}_{2\times4}$			$CF^{EU}_{2\times5}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	0.370 (2.40)	0.438 (2.82)	0.528 (3.11)	0.427 (2.62)	0.484 (2.93)	0.543 (2.98)	0.501 (2.69)	0.574 (3.06)	0.635 (3.00)
MKT	−0.027 (−0.55)	0.001 (0.02)	−0.018 (−0.50)	−0.045 (−0.93)	−0.018 (−0.46)	−0.030 (−0.75)	−0.087 (−1.62)	−0.062 (−1.43)	−0.074 (−1.66)
SMB		−0.320 (−2.95)	−0.292 (−2.61)		−0.331 (−2.91)	−0.313 (−2.63)		−0.370 (−2.92)	−0.351 (−2.66)
HML		0.108 (0.80)	0.015 (0.11)		0.122 (0.88)	0.061 (0.42)		0.144 (0.91)	0.081 (0.47)
CMA		0.312 (1.71)	0.391 (2.15)		0.307 (1.63)	0.358 (1.87)		0.279 (1.16)	0.332 (1.33)
RMW		0.050 (0.29)	0.023 (0.14)		0.095 (0.53)	0.078 (0.44)		0.55 (0.28)	0.037 (0.19)
MOM			−0.103 (−1.32)			−0.068 (−0.85)			−0.070 (−0.79)
R^2_{adj}	-0.00	0.29	0.30	0.01	0.26	0.27	0.03	0.26	0.26
No. Obs.	114	114	114	114	114	114	114	114	114

Note: We show estimates of spanning regressions of the circularity factor for various sorts on the Fama and French (2015) 5-Factor + Carhart (1997) Momentum-Factor. We report *t-statistics* in parentheses.
Standard errors are adjusted for heteroskedasticity and autocorrelation.

4 Alternative Portfolio Sorts

Soebhag et al. (2023) remark that the particular approach taken towards portfolio creation can have a huge impact on the factor itself. We thus dedicate this section to two alternative ways of constructing CF. In Section 4.1 we assign stocks *independently* into size and circularity categories. In Section 4.2 we opt for a univariate sorting based on CS only.

4.1 Independent Sorting

As alluded to earlier, sorting stocks *independently* along several dimensions, and then constructing portfolios based on their intersection, runs at the risk of ending up with sparsely populated, and hence, poorly diversified portfolios.

In order to get an idea as to what extent this shall be a concern in our case, we report the average number of firms within each portfolio across our sample period in Table 5. The "size-effect" is clearly visible. For the European market (upper panel), the average number of firms in the Big-CS_{High} portfolios (lower-right corners) is roughly three times higher than the average number of firms in the Small-CS_{High} portfolios (upper-right corners) – while the reverse is true for the Small-CS_{Low} and Big-CS_{Low} portfolios. This pattern can also be observed – in pretty similar magnitude – for the U.S.

market. Yet, none of the portfolios is (on average) close to entirely empty, with the (on average) least populated portfolio (31 firms) being the Small-CS_{High} portfolio of the 2×5 sort in the European market. Still, this number is larger than the cut-off of 10 firms in Feng et al. (2020).

Table 5: Average Number of Firms

	2 × 3 Sorts			2 × 4 Sorts				2 × 5 Sorts				
	Market: EU-15 + Switzerland											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	155	149	56	132	108	77	43	107	93	75	54	31
Big	61	139	159	49	72	102	136	37	51	69	90	113
	Market: U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	273	285	88	233	198	151	64	190	164	145	101	46
Big	114	232	299	90	125	172	259	68	94	113	157	212
	Market: EU-15 + Switzerland + U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	424	419	163	358	299	221	127	293	252	210	157	94
Big	180	385	440	145	203	281	375	109	150	192	245	308

Note: The three panels show the average number of firms (rounded to the nearest integer) for each portfolio over the period July 2013 to December 2022.
We construct portfolios based on an *independent* sorting according to a firm's size (market capitalization) and circularity score (CS). That is, we sort firms into two size portfolios (small or big, for which the breakpoint is the cross-sectional median in a given year t). Simultaneously, we sort firms into tertiles, quartiles, respectively quintiles, based on their circularity score. We construct portfolios based on the intersection of the two size and three, respectively four and five, circularity score groups.

For the independently sorted portfolios, Table 6 shows the corresponding excess returns, as well as the *t-statistic* and annualized Sharpe Ratio for the long-short strategy. The overall story is the same as for conditional sorts – yet with a few tweaks here and there. The return differential of a CS_{High} - CS_{Low} portfolio is essentially flat as soon as U.S. companies are involved. This strategy is only profitable – and stands the test against statistical significance – in the European market. Nevertheless, the unconditionally expected returns 45 BP, 51 BP, and 48 BP have noticeably increased relative to the 36 BP, 40 BP, and 46 BP for the conditional sorts in Tables 2 and 3.

Table 6: Average Monthly Excess Portfolio Returns

	2 × 3 Sorts			2 × 4 Sorts				2 × 5 Sorts				
	Market: EU-15 + Switzerland											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	0.35	0.57	0.87	0.28	0.58	0.70	0.82	0.30	0.53	0.51	0.85	0.69
Big	0.23	0.61	0.61	0.13	0.61	0.59	0.61	0.07	0.66	0.50	0.58	0.64
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	0.45	2.28	0.74	0.51	2.35	0.76			0.48	1.92	0.62	
	Market: U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	0.88	0.83	0.91	0.88	0.84	0.87	0.85	0.81	0.94	0.79	0.87	0.89
Big	0.86	0.85	0.88	0.85	0.93	0.88	0.84	0.89	0.80	0.72	1.02	0.82
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	0.02	0.14	0.04	-0.02	-0.11	-0.04			0.00	0.01	0.00	
	Market: EU-15 + Switzerland + U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
Small	0.81	0.73	0.74	0.78	0.76	0.74	0.73	0.81	0.76	0.71	0.75	0.72
Big	0.78	0.76	0.73	0.81	0.60	0.84	0.73	0.81	0.82	0.80	0.63	0.77
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	-0.06	-0.30	-0.10	-0.07	-0.33	-0.11			-0.07	-0.31	-0.10	

Note: The three panels show average monthly value-weighted excess portfolio returns for the period July 2013 to December 2022. The risk-free rate applied to portfolios in *Market: EU-15 + Switzerland + U.S.*, is the simple average of the European and U.S. risk-free rate.
We construct portfolios based on an *independent* sorting according to a firm's size (market capitalization) and circularity score (CS). That is, we sort firms into two size portfolios (small or big, for which the breakpoint is the cross-sectional median in a given year t). Simultaneously, we sort firms into tertiles, quartiles, respectively quintiles, based on their circularity score. We construct portfolios based on the intersection of the two size and three, respectively four and five, circularity score groups.
$E[r^e]$ denotes the expected excess return of buying the two CS_{High} portfolios and shorting the two corresponding CS_{Low} portfolios. *t-stat* is the corresponding t-statistic and SR^A denotes the annualized Sharpe Ratio.
Numbers are in percent, such that $0.10 \equiv 10$ basis points (BP).

Yet, the independently sorted returns lose on statistical significance, which is particularly evident for the 2×5 sorts: sliding from 2.33 in Table 3 to only 1.92 in Table 6.

Spanning regressions in Table 7 reveal familiar patterns. The coefficient of interest, α, is again statistically significant across all models and sorts, and close to the 3.00-boundary for the five- and six-factor models. Yet, the 2×5 sorts in Columns 7 through 9 give in to the 2×3 and 2×4 sorts, as the *t-statistic* drops markedly. The share of variance explained by the multi-factor models also slightly increases to about one-third relative to the conditionally constructed CF^{EU} as reported in Table 4.

Again the size factor, SMB, stands out as playing an important role in explaining the dynamics of CF^{EU}, while the value factor, HML, steps up, but the investment factor, CMA, struggles to keep its statistical significance. Interestingly, the 2×5 sorted CF^{EU} also seems to load on momentum factor (MOM), with the negative prefix indicating that CF^{EU} conforms with buying previous losers and shorting previous winners, that is CF^{EU} goes against the short-term trend.

Table 7: Spanning Regressions

	$CF^{EU}_{2\times3}$			$CF^{EU}_{2\times4}$			$CF^{EU}_{2\times5}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	0.478 (2.54)	0.513 (3.08)	0.543 (2.96)	0.537 (2.63)	0.618 (3.42)	0.69 (3.39)	0.477 (1.96)	0.497 (2.31)	0.647 (2.71)
MKT	−0.058 (−1.17)	−0.058 (−1.19)	−0.065 (−1.233)	−0.047 (−0.80)	−0.016 (−0.37)	−0.032 (−0.64)	0.000 (0.01)	0.012 (0.05)	−0.019 (−0.40)
SMB		−0.392 (−3.59)	−0.383 (−3.37)		−0.448 (−3.54)	−0.426 (−3.25)		−0.395 (−2.87)	−0.348 (−2.34)
HML		0.333 (2.04)	0.301 (1.65)		0.217 (1.31)	0.142 (0.83)		0.383 (2.17)	0.228 (1.13)
CMA		0.172 (0.74)	0.199 (0.81)		0.412 (1.76)	0.475 (1.98)		0.439 (1.60)	0.570 (1.98)
RMW		0.238 (1.22)	0.229 (1.18)		0.140 (0.68)	0.118 (0.59)		0.406 (0.174)	0.361 (1.60)
MOM			−0.035 (−0.40)			−0.083 (−0.83)			−0.172 (−1.89)
R^2_{adj}	0.01	0.31	0.31	0.00	0.34	0.34	-0.01	0.31	0.33
No. Obs.	114	114	114	114	114	114	114	114	114

Note: We show estimates of spanning regressions of the circularity factor for various sorts on the Fama and French (2015) 5-Factor + Carhart (1997) Momentum-Factor. We report *t-statistics* in parentheses.
Standard errors are adjusted for heteroskedasticity and autocorrelation.

In general, the results of constructing CF^{EU} from independent sorts on size and CS, echo the findings of the conditional sorting in sections 3.2 and 3.3: The CF^{EU} uncovers an anomaly in the European stock market that is not to be explained by a set of prominent asset-pricing models and delivers statistically and economically meaningful expected excess returns.

4.2 Univariate Sorting

Lastly, we show results for constructing CF based on a univariate sorting on CS only. We thus consciously neglect the size-bias within ESG ratings as mentioned in section 3. This will result in the CS_{High} portfolio being composed of larger firms relative to the CS_{Low} portfolio. A profitable long-short strategy of CS_{High} - CS_{Low} will thus have to overcome the SMB effect – small firms outperforming large firms. As a consequence, economic and statistical significance of such a strategy may drop with respect to a strategy built on conditional, respectively independent, sorts. We present average monthly excess returns of the corresponding portfolios in Table 8.

As conjectured, the CF^{EU} suffers from a strongly diminished *t-statistic*, with none of the different sorts making it into the territory north of 2.00. The expected excess return of the hedging portfolio is however in the ballpark of previous sortings, or even surpasses previous estimates as in the case of the 1×5 sort.

Table 8: Average Monthly Excess Portfolio Returns

	1×3 Sorts			1×4 Sorts				1×5 Sorts				
	Market: EU-15 + Switzerland											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
	0.25	0.61	0.61	0.15	0.61	0.60	0.62	0.10	0.64	0.50	0.59	0.64
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	0.37	1.45	0.47	0.47	1.73	0.56			0.53	1.66	0.54	
	Market: U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
	0.86	0.84	0.87	0.84	0.91	0.87	0.84	0.87	0.83	0.72	1.01	0.82
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	0.01	0.06	0.02	0.00	-0.01	0.00			-0.04	-0.18	-0.06	
	Market: EU-15 + Switzerland + U.S.											
	CS_{Low}	CS_{Med}	CS_{High}	CS_{Low}	CS_{50}	CS_{75}	CS_{High}	CS_{Low}	CS_{40}	CS_{60}	CS_{80}	CS_{High}
	0.77	0.75	0.73	0.80	0.61	0.83	0.73	0.80	0.80	0.79	0.63	0.77
	$E[r^e]$	*t-stat*	SR^A	$E[r^e]$	*t-stat*	SR^A			$E[r^e]$	*t-stat*	SR^A	
CS_{High}- CS_{Low}	-0.04	-0.18	-0.06	-0.07	-0.34	-0.11			-0.03	-0.12	-0.04	

Note: The three panels show average monthly value-weighted excess portfolio returns for the period July 2013 to December 2022. The risk-free rate applied to portfolios in *Market: EU-15 + Switzerland + U.S.*, is the simple average of the European and U.S. risk-free rate.
We construct portfolios based on a univariate sorting according to a firms circularity score (CS) only.
$E[re]$ denotes the expected excess return of buying the CS_{High} portfolio and shorting the corresponding CS_{Low} portfolio. *t-stat* is the corresponding t-statistic and SR^A denotes the annualized Sharpe Ratio.
Numbers are in percent, such that $0.10 \equiv 10$ basis points (BP).

The spanning regressions in Table 9 still have the majority of α achieving a *t-statistic* north of 2.00. Nonetheless, some additional observations are noteworthy. Especially $CF^{EU}_{1\times3}$ seems to be more exposed to market wide movements, yet loading with a negative sign, suggesting the circularity factor to be some kind of hedge against systematic risk. However, the unconditionally expected excess return for $CF^{EU}_{1\times3}$ was not statistically significantly different from zero. Interestingly, this exposure to systematic market risk vanishes in columns (5) - (9). SMB plays a dominant role, which does not come as a surprise and validates our approach to go for double sorted portfolios on size and CS when constructing CF.

For the first time, the profitability factor, RMW, appears to play a statistically significant role to explain movements in CF – however for the 1×3 sorting only. The positive sign, nevertheless, plays into the story of firms with high CS being expected to generating higher cash-flows in the future.

Table 9: Spanning Regressions

	$CF^{EU}_{1\times3}$			$CF^{EU}_{1\times4}$			$CF^{EU}_{1\times5}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	0.427	0.413	0.437	0.525	0.578	0.630	0.594	0.607	0.74
	(1.79)	(2.11)	(1.88)	(2.02)	(2.53)	(2.39)	(1.74)	(2.16)	(2.11)
MKT	−0.120	−0.112	−0.117	−0.106	−0.049	−0.060	−0.116	−0.064	−0.091
	(−2.22)	(−1.81)	(−1.83)	(−1.81)	(−1.06)	(−1.17)	(−1.52)	(−0.98)	(−1.40)
SMB		−0.643	−0.635		−0.698	−0.681		−0.738	−0.697
		(−4.73)	(−4.48)		(−4.66)	(−4.33)		(−4.14)	(−3.63)
HML		0.358	0.333		0.158	0.103		0.217	0.080
		(1.69)	(1.43)		(0.89)	(0.52)		(0.92)	(0.28)
CMA		0.019	0.040		0.401	0.448		0.376	0.492
		(0.06)	(0.12)		(1.55)	(1.65)		(1.15)	(1.32)
RMW		0.459	0.451		0.301	0.285		0.466	0.426
		(1.84)	(1.79)		(1.36)	(1.29)		(1.56)	(1.42)
MOM			−0.027			−0.060			−0.152
			(−0.27)			(−0.58)			(−1.16)
R^2_{adj}	0.04	0.24	0.24	0.02	0.27	0.26	0.02	0.20	0.20
No. Obs.	114	114	114	114	114	114	114	114	114

Note: We show estimates of spanning regressions of the circularity factor for various sorts on the Fama and French (2015) 5-Factor + Carhart (1997) Momentum-Factor. We report *t-statistics* in parentheses.
Standard errors are adjusted for heteroskedasticity and autocorrelation.

The lessons learned from this section are twofold: first, the results of the sorting stocks *independently* on market-capitalization and CS echo the findings from *conditionally* sorted portfolios. Second, the statistical significance of CF^{EU} takes a hit when constructing portfolios based on CS only. Lastly, spanning regressions of circularity factors, constructed from *univariately* sorted portfolios, on multivariate factor models reveal a strong exposure to SMB, confirming the choice of accounting for a firm's size when constructing the circularity factor.

5 A new Attraction in the Zoo?

In the previous sections, we have introduced CF as a profitable portfolio allocation strategy which buys stocks that score high on the circularity score, introduced by Zara and Ramkumar (2022), and shorts companies that range in the left tail of the CS distribution. However, such a strategy is only profitable, i.e. generating returns that are both economically and statistically significantly higher than the risk-free rate, can only be found in the European market. In the U.S. market, in contrast, this anomaly is not existent – up to now – as a long-short strategy does not provide neither statistically nor economically significant excess returns.

In spanning regressions, we have put $\mathrm{CF}^{\mathrm{EU}}$, i.e. the European descendant of CF, to the test against the arguably most prominent set of factor models: the CAPM (Sharpe, 1964; Lintner, 1965), the Fama and French (2015) five-factor model, and a six-factor model that augments the latter by the Carhart (1997) momentum-factor.

These spanning regressions is that they tell us whether any linear combination of already existing and well-established anomalies renders $\mathrm{CF}^{\mathrm{EU}}$ obsolete, and at the same time give us an idea to which extent $\mathrm{CF}^{\mathrm{EU}}$ is exposed – respectively, captures – additional sources of risk beyond the one associated with the transition to a more sustainable – and in particular, a more *circular* – economy. However, spanning regressions do not tell us, whether $\mathrm{CF}^{\mathrm{EU}}$ does really add any new information that helps with pricing the cross-section of average stock returns. Hence, $\mathrm{CF}^{\mathrm{EU}}$ needs to be put to another test, which we design in the spirit of Feng et al. (2020) as follows:

$$r_t = E(r_t) + \mathbf{F}_t \beta' + CF_t^{\mathrm{EU}} \gamma + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma), \tag{4}$$

where r_t is an $N_t \times 1$ dimensional vector of returns from N test assets at time t. These "test assets" may either be single stock returns or returns of whole portfolios. Following the literature, the latter will constitute our set of test assets $\mathbb{P} = \{1, \ldots, N^{\mathbb{P}}\}$. $\mathbf{F}_t$ is a $1 \times N^F$ dimensional vector of N^F factors, i.e. returns of a set of characteristically-managed portfolios $\mathbb{F}$, and β is the corresponding $1 \times N^F$ dimensional vector of factor loadings. CF_t^{EU} is the observed return on the circularity factor at time t and γ the corresponding loading.

The set of factors, $\mathbb{F}$, is thus intended to span the true underlying stochastic discount factor (SDF) that prices the cross-section of expected stock returns. However, restricting this set to six factors only – as we did in the spanning regressions – appears to be a very strong assumption, given the myriad of asset-pricing anomalies that have been introduced in the asset-pricing literature since the seminal paper of Fama and French (1992), who extended the CAPM to a three-factor model. This inflation of factors has lead Cochrane (2011) to coin the term "factor zoo". Yet, this didn't bring the hunt for new factors to a halt, and the zoo of factors has enjoyed regular additions ever since (Harvey et al., 2015; Feng et al., 2020; Jensen et al., 2023).

Along these lines, for the CF^{EU} to be considered as a new addition to the already existing zoo, it has to, first, price the cross-section of stock returns, and second, to stand out among all the other already existing factors. Conducting such a test then requires two key ingredients: first, adequate test portfolios, and second, an appropriate testing procedure.

Regrading the former, we take $N^{\mathbb{P}} = 220$ portfolios prepared exclusively for the European market from Kenneth R. French's website[5]. More specifically, the set of test portfolios, $\mathbb{P}$, is composed of: 2×3 portfolios sorted by size and book-to-market ratio, 5×5 portfolios sorted by size and book-to-market ratio, 2×3 portfolios sorted by size and operating profitability, 5×5 portfolios sorted by size and operating profitability, 2×3 portfolios sorted by size and investment, 5×5 portfolios sorted by size and investment, 2×3 portfolios sorted by size and momentum, 5×5 portfolios sorted by size and momentum, $2 \times 4 \times 4$ portfolios sorted by (i) size, (ii) book-to-market, and (iii) operating profitability, $2 \times 4 \times 4$ portfolios sorted by (i) size, (ii) book-to-market, and (iii) investment, and lastly, $2 \times 4 \times 4$ portfolios sorted by (i) size, (ii) operating profitability, and (iii) investment.

We source the set of incumbent factors ($\mathbb{F}$), which CF^{EU} has to stand out against, from Jensen et al. (2023) (JKP).[6] As our circularity factor is based on the European market, these JKP factors should also be in line with covering a similar geographic area. As the JKP factors are not available for the European region, we take the factors for *developed markets* and clean them from non-European constituents.[7] That is, the set of European JKP factors ($\mathbb{F} = \mathbb{F}^{EU} = \{1, ..., 153\}$) is the residual of the following simple linear regression:

$$f_{it}^{D} = \sum_{n=1}^{N} \beta_n f_{it}^{n} + \varepsilon_{it} , \quad i \in \mathbb{F}, n \in \{D \notin \{EU_{15}, CHE\}\} \tag{5}$$

where f_{it}^{D} is factor $i = 1, ...153$ for developed markets, and f_{it}^{n} is factor $i = 1, ...153$ for country n, which is among the set of developed market economies according to Jensen et al. (2023), but does not belong to the group of EU-15 and Switzerland. After cleaning f_{it}^{D}, our set of "European" factors $\mathbb{F} = 153$ only misses Luxembourg and Greece compared to the set of EU-15 countries plus Switzerland, which form the basis for our circularity factor CF^{EU}. We restrict the sample period in Equation (5) to match the period over which we calculate CF^{EU}: July 2013 till December 2022.

With about $N^{\mathbb{F}} + CF^{EU} = 154$ asset-pricing anomalies and $N^{\mathbb{P}} = 220$ test portfolios at hand, we are now ready to put CF^{EU} to the final test. However, the dimension of this data set makes simple OLS a poor modeling choice. We are close to running out of degrees of freedom and inference becomes unreliable. Moreover, some constituents of $\mathbb{F}$ might be irrelevant for pricing our test assets. Hence, a parsimonious model might be preferable. One of the most popular econometric tools to achieve such variable selection is the *least absolute shrinkage and selection operator* (LASSO) (Tibshirani,

[5]See Kenneth R. French's Data Library.
[6]See: jkpfactors.com.
[7]See Appendix A for a list of countries that constitute the JKP factors for *developed markets*.

1996). Yet, just applying the LASSO on a regression of $\mathbb{P}$ on $\mathbb{F} \cup \mathrm{CF}^{\mathrm{EU}}$ does not lead to reliable estimates neither, due to its weaknesses in finite samples, which are further amplified in our setting with $\mathbb{P} = 220$ only. That is, in finite samples, LASSO struggles to uncover the true underlying SDF (Feng et al., 2020).

To still make use of the appealing features of the LASSO, we adopt the procedure proposed by Feng et al. (2020). Their algorithm combines the *double-selection LASSO* of Belloni et al. (2013) with conventional two-pass regressions à la Fama and MacBeth (1973). The particular steps are outlined in Appendix B.1. The final parameter of interest in Algorithm (1) is λ_g, i.e. the coefficient on the covariance between our test asset returns and $\mathrm{CF}^{\mathrm{EU}}$, in the final cross-sectional OLS regression (Step 5 in Algorithm (1)) of average portfolio returns on covariances between portfolio returns and a select set of factors $\mathbb{F}^* \cup \mathrm{CF}^{\mathrm{EU}}$, where $\mathbb{F}^*$ is a subset of our initial factor zoo $\mathbb{F}$. Feng et al. (2020) show that λ_g then follows a normal distribution, such that

$$\lambda_g \sim N(0, \Pi) ,$$

where Π is estimated as outlined in Feng et al. (2020) – or for convenience in Appendix B.2.

We run this exercise for $\mathrm{CF}^{\mathrm{EU}}$ based on conditional, independent and univariate portfolio sorts. For better comparison, we do as in Feng et al. (2020), and compute $\widetilde{\lambda}_g$, a scaled version of $\widehat{\lambda}_g$, such that it resembles a *unit beta* exposure to the corresponding $\mathrm{CF}^{\mathrm{EU}}$:

$$\widetilde{\lambda}_{CF} = \widehat{\lambda}_g \, \widehat{\sigma}^2_{\mathrm{CF}} ,$$

where $\widehat{\sigma}^2_{\mathrm{CF}}$ is the sample variance of $\mathrm{CF}^{\mathrm{EU}}$. In Table 10 we show the resulting $\widetilde{\lambda}_{CF}$, its corresponding *t-statistic*, and the number of factors, N^{OLS}, that entered the final OLS estimation (Step 5 in Algorithm (1)) as the competitors to $\mathrm{CF}^{\mathrm{EU}}$ for pricing the cross-section of test portfolios $\mathbb{P}$.

Table 10: The European Circularity Factor and the Factor Zoo

	$N^S \times 3$ Sorts			$N^S \times 4$ Sorts			$N^S \times 5$ Sorts		
	$\widetilde{\lambda}_{CF}$ (BP)	*t-stat*	N^{OLS}	$\widetilde{\lambda}_{CF}$ (BP)	*t-stat*	N^{OLS}	$\widetilde{\lambda}_{CF}$ (BP)	*t-stat*	N^{OLS}
Conditional Sorting ($N^S = 2$)	-107	-2.92***	32	-95	-3.06***	32	-100	-2.86***	36
Independent Sorting ($N^S = 2$)	-115	-3.28***	34	-120	-2.58*	35	-160	-2.80***	35
Univariate Sorting ($N^S = 1$)	-84	-1.95*	43	-120	-2.26**	39	-176	-1.71*	42

Note: We show the SDF loading of the European circularity factor ($\mathrm{CF}^{\mathrm{EU}}$) for various portfolio sorts and the corresponding *t-statistic*. $\widetilde{\lambda}_{CF}$ is the SDF loading, scaled to a unit beta exposure of the test-portfolios to $\mathrm{CF}^{\mathrm{EU}}$.
N^S indicates the number of size groups applied in each sorting procedure.
N^{OLS} is the number of factors that were selected in Step 1a and Step 1b, and hence enter the OLS regression of Step 2 in addition to the circularity factor.

Our benchmark specification – the conditional 2×3 sorting – has an $\widetilde{\lambda}_{CF} = -107$, indicating that a portfolio with one unit of a univariate beta exposure to CF^{EU}, generates an average excess return of -107 BP. This elasticity is highly statistically significant with a *t-statistic* of -2.92. Sorting stocks into quartiles or quintiles instead of tertiles only, does not alter the statistical significance, with *t-statistics* for all conditional sorts ranging in the neighborhood of 3.00.Sorting stocks independently on size and CS leads to slightly more heterogeneity across the three panels. Loadings now range from -115 BP to -160 BP. Constructing CF^{EU} based on a univariate sort of CS only generates both the highest excess return (in absolute value) of -176 BP, but lingers on the edge of statistical significance.

In summary, Table 10 shows that CF^{EU} – a long-short portfolio of European firms with a high, respectively low, circularity score – does stand the test against a plethora of established factors and helps to price the cross-section of excess stock returns.

6 Conclusion

Economies all around the world are transitioning towards becoming "greener". Such a transition does not only imply achieving net-zero emissions by date X. If sustainability is taken seriously, we will have to transform our habitual linear consumption-based economy of produce-consume-dispose into a more circular model of waste prevention, reuseability, re-manufacturing and upcycling. Such a "Circular Economy" necessitates big structural changes that can disrupt industries, but also offer new possibilities.

Investors may want to hedge against the risks that come with such a transition, as a company that runs on finite resources and does not conform with circular practices either has to ultimately face ever rising costs of production or will be restricted in its generation of cash flows.

We construct a hedging portfolio that – controlling for firm size – buys stocks with high CS and shorts those with low CS. Depending on the granularity of the splits, such a strategy generates a monthly expected excess return between 36 BP and 51 BP, with annualized Sharpe Ratios of 0.72 and 0.76. Yet, these numbers only hold for the European market. In the U.S. market, such a portfolio does not deliver returns that are neither statistically significant nor economically meaningful in any way.

These observations speak to the different institutional settings across the two markets, and counters the argument in the literature that hitherto observed ESG outperformance is not because of higher expected returns going forward, but rather due to an increased accumulation of climate related negative news within the respective sample period (Giglio et al., 2021; Pastor et al., 2022). It rather speaks to the argument brought forth in Hsu et al. (2023) that a regulatory regime shift – here, the European regulatory push towards a circular economy with the implementation of CEPA in December 2015 – will impact firm profitability.

These considerations might suggest a close alignment between our European circularity factor (CF^{EU}) and and the profitability factor of Hou et al. (2015). Yet, spanning regressions reveal that RMW does not play any statistically significant role in explaining the movements in CF^{EU}.

We then put CF^{EU} to the test against the zoo of factors in pricing the cross-section of European stock returns. Adapting the testing procedure proposed by Feng et al. (2020), we find CF^{EU} to be a highly statistically significant predictor. Testing portfolios with a unit beta exposure to CF^{EU}, generate an average monthly excess return of around -100 BP and corresponding *t-statistics* ranging around 3.00.

Lastly, one may criticize these results along several grounds: first, we construct CS based on ESG-related information, and the caveats that come with these ratings is no news in the literature (Dimson et al., 2020; Christensen et al., 2021; Berg et al., 2022a,b; Avramov et al., 2022). Nevertheless, these ratings are the industry standard and form the basis for investment activities day in and day out. Second, the asset-pricing literature, in the spirit of Fama and French (1992), usually motivate their factor by its performance in the U.S. market using a sample of monthly stock-returns between the 1960s and the present day. Our procedure is, on the one hand, limited by sustainable investing being a rather nascent field, with practices on a broad scale merely picking up after the Great Financial Crisis. Even though the implementation of the *Non-financial Reporting Directive* by the European Commission in 2014 required large listed companies with more than 500 employees to publish reports on social and environmental issues, this legislative still granted companies a large degree of flexibility in judging which information to disclose. This does not only restrict the dimension of our cross-section as circularity-related information might be insufficient, but malpractices, such as green-washing, cannot be ruled out neither.

Nonetheless, looking forward, on both sides of the Atlantic, the coming years will see a variety of regularity changes that regards the mandatory reporting of ESG-, and thus, circularity-related disclosures. It will thus be interesting to see how the circularity factor will evolve in the future. A dilemma that much of the academic research in the factor-investing sphere is plagued by, is the fact that once a factor is published, it ceases to exist. In light of the upcoming regulatory changes – especially in the U.S. – the CF^{US} might take the other route, and only emerge after the CF^{EU} came into existence.

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A JKP-Factors: Supplementary Information

For section 5, we take the set of factors $\mathbb{F}$ from Jensen et al. (2023). The set of countries that constitutes the developed markets' factors $\mathbb{F}^D$ reads according to the reference paper as follows (sorted by number of stocks that enter the factor calculation in Jensen et al. (2023)):

United States, Japan, Hong-Kong, **United Kingdom**, **France**, **Germany**, Canada, Australia, **Switzerland**, **the Netherlands**, **Sweden**, **Italy**, **Spain**, **Denmark**, Singapore, **Belgium**, Norway, **Finland**, Israel, **(Republic of) Ireland**, New Zealand, **Austria**, **Portugal**.

Countries in **bold** represent those economies that belong to the group of the EU-15 plus Switzerland – that particular set that forms the basis for our European circularity factor CE^{EU}.

B The Double-Selection LASSO

In this section – for convenience – we outline the *Double-Selection LASSO* algorithm and the corresponding asymptotics, which we borrowed to a very large extent from Feng et al. (2020).

B.1 The Double-Selection LASSO: Algorithm

To comply with the notation of the original paper, we denote (i) R_p as the T-dimensional column-vector of returns with elements $r_{p,t}$ of test portfolio p, such that R is the $T \times N^P$ dimensional matrix of $N^P = 220$ test portfolio returns, (ii) H as the $T \times N^H$ matrix of $N^H = 153$ JKP factors ($\mathbb{F}$), and (iii) G as our $T \times N^G$ matrix containing only CF^{EU}, such that $N^H = 1$.[8] Furthermore, let $\odot$ denote the element-wise product.

Steps 3 and 4 obviously leave the modeler with some degree of freedom, in the sense that she has to take a stand on the degree of regularization in the form of choosing an adequate penalty κ_0 and κ_1 respectively. In the spirit of Feng et al. (2020), we thus run 200 iterations of a 10-fold cross-validation of Step 3 and Step 4 respectively, and choose κ_0 and κ_1 as the average κ of the corresponding 200 iterations.

B.2 The Double-Selection LASSO: Asymptotic Distribution

[8] As we only test a single factor (CF^{EU}), this would imply $j = 1$ in Feng et al. (2020).

Algorithm 1 ***Double Selection LASSO** (Feng et al., 2020)*

1: Set:

$$
\begin{aligned}
\bar{r}_p &= \frac{1}{T}\sum_{t=1}^{T} r_{p,t} \quad \text{for } p \in \mathbb{P} \\
\bar{r} &= [\bar{r}_1, \bar{r}_2, \ldots, \bar{r}_{N^P}] \\
\bar{R}_p &= \left[r_{p,1}-\bar{r}_p, r_{p,2}-\bar{r}_p, \ldots, r_{p,T}-\bar{r}_p\right] \\
\bar{R} &= [\bar{R}_1, \bar{R}_2, \ldots, \bar{R}_{N^P}]
\end{aligned}
$$

$$
\left.
\begin{aligned}
\bar{x}_n &= \frac{1}{T}\sum_{t=1}^{T} x_{n,t} \quad \text{for } n \in N^X \\
\bar{X}_n &= [x_{n,1}-\bar{x}_n, x_{n,2}-\bar{x}_n, \ldots, x_{n,T}-\bar{X}_n] \\
\bar{X} &= [\bar{X}_1, \bar{X}_2, \ldots, \bar{X}_{N^X}]
\end{aligned}
\right\} \quad \text{with } X = \{H, G\}
$$

$$
\begin{aligned}
\widehat{C}_x &= \widehat{\text{Cov}}\,(r_t, x_t) \;=\; T^{-1}\bar{R}^{\mathrm{T}}\bar{X} \quad \text{with } x \in \{H, G\} \\
\widehat{\sigma}_x^2 &= \widehat{\text{Var}}\,(x_t) \quad \text{with } x \in H
\end{aligned}
$$

2: Factor-specific weights:

$$
\begin{aligned}
\omega_h &= \frac{1}{N^P}\left\| \widehat{C}_h \odot \widehat{\sigma}_h^2 \right\|_2^2 \\
\omega &= [\omega_1, \ldots, \omega_{N^H}] \odot \left(\frac{1}{N^H}\sum_{h=1}^{N^H} \omega_h\right)^{-1}
\end{aligned}
$$

3: Cross-Sectional LASSO: average returns on sample covariances between JKP factors and returns

$$
\min_{\gamma,\,\lambda}\left\{\frac{1}{N^P}\left\|\bar{r}-\gamma-\widehat{C}_h\lambda\right\|^2 + \kappa_0 \left\|\lambda\omega^{\mathrm{T}}\right\|_1\right\}
$$

4: Cross-Sectional LASSO: sample covariances between $\mathrm{CF}^{\mathrm{EU}}$ and returns on sample covariances between JKP factors and returns

$$
\min_{\phi,\,\delta}\left\{\frac{1}{N^P}\left\|\widehat{C}_g-\phi-\widehat{C}_h\delta\right\|^2 + \kappa_1 \left\|\delta\omega^{\mathrm{T}}\right\|_1\right\}
$$

5: Cross-Sectional OLS:

$$
\left(\widehat{\gamma}_0,\, \widehat{\lambda}_g,\, \widehat{\lambda}_h\right) = \underset{\gamma_0,\,\lambda_g,\,\lambda_h}{\operatorname{argmin}} \left\|\bar{r}-\gamma_0-\widehat{C}_g\lambda_g-\left(\widehat{C}_h \odot \mathbf{1}_{\lambda\cup\delta\neq 0}\right)\lambda_h\right\|^2
$$