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Decomposing Differences in Quantile Portfolio Returns betweenNorth America and Europe Using Recentered Influence Function Regression

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Abstract

Huang (2018) decomposes the differences in quantile portfolio returns using distribution regression. The main issue of using distribution regression is that the decomposition results are path dependent. In this paper, we are able to obtain path independent decomposition results by combining the Oaxaca-Blinder decomposition and the recentered influence function regression method. We show that aggregate composition effects are all positive across quantiles and the market factor is the most significant factor which has detailed composition effect monotonically decreasing with quantiles. The main decomposition results are consistent with Huang (2018)

Keywords: Decomposition Analysis, Oaxaca-Blinder Decomposition, Five-factor Asset Pricing Model, Recentered Influence Function Regression, Unconditional Quantile regression.

I.   Introduction

To the best of our knowledge, Huang (2018) is the first one to decompose the differences between two portfolio returns into Fama and French (2015) five factors.Huang (2018) shows that the market factor contributes the most to the quantiledifferencesin theportfolio returns between North America and Europe by combining the Oaxaca-Blinder decomposition and distribution regression. As Huang (2018)points out their results about quantile differences suffer the path dependent problem. The main disadvantage of using distribution regression to decompose the quantile differences is that the results are path dependent, that is, the order of decomposition affects the estimates of the detailed components. Thus, a more attractive approach should be able to decompose the quantile differences and be path independent as well. In this paper, we apply the recentered influence function (RIF) regressions method, which is able to obtain path independent estimates of the detailed components for the quantile differences.[1]RIF regression is developed by Firpo, Fortin and Lemieux (2009) (see two interesting applications, Borah and Basu(2013) and Maclean, Webber, and Marti (2014)). [2]Combining RIF regression with traditional Oaxaca-Blinder decomposition (Oaxaca 1973 and Blinder 1973), we do the detailed decomposition for the differences in quantile portfolio returns and obtain path independent results.

For the purpose of comparing the results, we use the same data as Huang (2018). We will briefly describe the data in Section 4.We show that aggregate composition effects across all quantiles are positive and the market factor is the most

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[1]As stated in Fortin, Lemieux, and Firpo (2011), RIF regressions and the distribution regression approach of Chernozhukov, Fernández-Val, and Melly (2013) are closely connected, both of which are estimated for explaining the determinants of the proportion of outcome variable less than a certain value. The main difference is that distribution regression inverts globally the estimates of models for proportions into quantiles but RIF regressions locally invert the proportions estimates into quantiles. Thus, although decomposition results from RIF regressions are path independent, the limitation is that we do not know how good the approximation is in the locally invertion of proportion into quantiles.

[2]RIF is also named as unconditional quantile regression when the recentered function is for quantile. Thus, in this paper we interchangeably use RIF and unconditional quantile regression.

significant factor.These results are consistent with Huang (2018). The detailed composition effects linked to the market factor are monotonically decreasing with quantiles.

We organize the rest of the paper as follows. Section 2 provides a brief literature review, especially focusing on the Fama and French's five-factor model. Decomposition using the RIF-regression method is presented in Section 3. Section 4 describes the data briefly. Section 5 presents the decomposition results. We conclude in Section 6.

II. Five-factor Model

There is much evidence that average stock returns are related to the market returns (Sharpe1964, Lintner 1965, Breeden 1979), size, value[3], (Banz 1981, Basu 1983, Rosenberg, Reid and Lanstein 1985), profitability (Novy-Marx 2013)and investment (Aharoni, Grundy, and Zeng2013).[4]Motivated by the evidence of Novy-Marx (2013) and Titman, Wei, and Xie(2004) and the dividend discount model, Fama and French (2015) establish the five-factor model by adding profitability and investment factors into the Fama and French (1993) three-factor model. Using international data, Fama and French (2017) show the empirical robustness of regional five-factor model in explaining the monthly excess portfolio returns, especially in North America and Europe capital markets. Fama and French's five-factor model is as follows,

$$R_{it} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (2.1)$$

In this equation, $R_{it}$is the return in excess of riskfree rate on portfolio ifor period t.[5]MKT_t is the excess return on the value-weighted market portfolio, SMB_t(Size factor) is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t(value factor) is the difference between the returns of high and low B/M stocks, RMW_t (profitability factor) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA_t (investment factor) is the difference between the returns on diversified portfolios of the stocks of low and high (conservative and aggressive) investment firms.[6]

III. RIF-regression Method

A RIF-regression is basically a standard regression with which the dependent variable is replaced by the recentered influence function of the statistic of interest. RIF-regression is quite related to distribution regression (Foresi and Peracchi 1995 and Chernozhukov, Fernández-Val,and Melly 2013) as we show below.[7] In this paper, we are interested in the recenteredinfluence function for quantiles. The recentered influence function for quantiles can be obtained by recentering the influence function.The influence function corresponding to the τthquantile of a variable, Y, is given by$(\tau - 1\{Y \le Q_\tau\})/f_Y(Q_\tau)$, where $1\{Y \le Q_\tau\}$ is an indicator function which is equal to 1 if Y is less or equal to τthquantile of the unconditional distribution of Y (Q_τ) otherwise zero. $f_Y(Q_\tau)$is the density of the marginal distribution of Y.Then, the recentered influence function for τthquantile can be written as

$$RIF(y, Q_\tau) = Q_\tau + \frac{\tau - 1\{y \le Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau} \cdot 1\{y \le Q_\tau\} + c_{2,\tau} \quad (3.1)$$

where$c_{1,\tau} = -1/f_Y(Q_\tau)$ and $c_{2,\tau} = Q_\tau + \tau/f_Y(Q_\tau)$. Except the constants $c_{1,\tau}$ and $c_{2,\tau}$, we can see that RIF is just an indicator variable $1\{y \le Q_\tau\}$, which makes the RIF-regression very similar to the distribution regression.To estimate RIF, we first compute the sample quantile $\widehat{Q_\tau}$and estimate the density at$\widehat{Q_\tau}$ using kernel methods. Then, by plugging in the estimates of the sample quantile $\widehat{Q_\tau}$and the density at $\widehat{Q_\tau}$into the equation 3.1, an estimate of the RIF of each observation is obtained.

In the paper,Y_{it} is the excess portfolio return on portfolio i in period t, $Y_{it} = R_{it}$. We can estimate$\widehat{RIF}_{it}(Y_{it}, Q_\tau)$ by using$\widehat{RIF}_{it}(Y_{it}, Q_\tau) = \hat{Q}_\tau + \frac{\tau - 1\{Y_{it} \le \hat{Q}_\tau\}}{\hat{f}_Y(Q_\tau)}$. We then regress $\widehat{RIF}_{it}(Y_{it}, Q_\tau)$on five factors as follows

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[3]Size is measured by market capitalization, price times shares outstanding. Value is book-to-market equity ratio, B/M.

[4]See also Breeden, Gibbons, and Litzenberger(1989), Reinganum(1981), Haugen and Baker (1996), Cohen, Gompers,

and Vuolteenaho(2002), Fairfield, Whisenant, and Yohn(2003), Titman, Wei, and Xie(2004),Fama and French (2006, 2008, 2016), Hou, Xue, and Zhang (2015).

[5]For monthly data, the riskfree rate is one-month Treasury bill rate.

[6]The details of the constructions of the portfolios and factors could be found in Fama and French (1993, 2015, 2017).

[7]A distribution regression is simply a linear regression of$1\{y \le Q_\tau\}$ on X when the linear probability model is used as the link function.

$$\widehat{RIF}_{it}(Y_{it}, Q_\tau) = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (3.2)$$

We simplify the model above by dropping the time and portfolio subscription and using g indicating North America or Europe. It follows

$$\widehat{RIF}_g = \alpha_g + X_g' \beta_g + \epsilon_g \quad (3.3)$$

Then the RIF-regression version of the Oaxaca-Blinder decomposition for τth quantile follows

$\hat{\Delta}_O^\tau = \overline{RIF}_a - \overline{RIF}_u$

$= (\overline{RIF}_a - \overline{RIF}_a^c) + (\overline{RIF}_a^c - \overline{RIF}_u)$

$= [(\hat{\alpha}_a + \bar{X}_a' \hat{\beta}_a) - (\hat{\alpha}_a + \bar{X}_u' \hat{\beta}_a)] + [(\hat{\alpha}_a + \bar{X}_u' \hat{\beta}_a) - (\hat{\alpha}_u + \bar{X}_u' \hat{\beta}_u)] \quad (3.4)$

$= \hat{\Delta}_C^\tau + \hat{\Delta}_S^\tau$

$= [(\bar{X}_{a1}' - \bar{X}_{u1}') \hat{\beta}_{a1} + \cdots + (\bar{X}_{a5}' - \bar{X}_{u5}') \hat{\beta}_{a5}] + [(\hat{\alpha}_a - \hat{\alpha}_u) + \bar{X}_{u1}'(\hat{\beta}_{a1} - \hat{\beta}_{u1}) + \cdots + \bar{X}_{u5}'(\hat{\beta}_{a5} - \hat{\beta}_{u5})]$

$= (\hat{\Delta}_C^1 + \cdots + \hat{\Delta}_C^5) + (\hat{\Delta}_S^\alpha + \hat{\Delta}_S^1 + \cdots + \hat{\Delta}_S^5)$

where $\overline{RIF}_a$ and $\overline{RIF}_u$ are the estimated mean $\widehat{RIF}$ of North America and Europe respectively. $\overline{RIF}_a^c$ is equal to $(\hat{\alpha}_a + \bar{X}_u' \hat{\beta}_a)$, which is $\overline{RIF}_a$ except with $\bar{X}_a'$ replaced by $\bar{X}_u'$. $\hat{\Delta}_C^\tau$ and $\hat{\Delta}_S^\tau$ are the estimates of aggregate composition and structure effects, equal to $[(\hat{\alpha}_a + \bar{X}_a' \hat{\beta}_a) - (\hat{\alpha}_a + \bar{X}_u' \hat{\beta}_a)]$ and $[(\hat{\alpha}_a + \bar{X}_u' \hat{\beta}_a) - (\hat{\alpha}_u + \bar{X}_u' \hat{\beta}_u)]$, respectively. The unexplained component, which is linked to the constant term, is estimated by $(\hat{\alpha}_a - \hat{\alpha}_u)$. The detailed composition and structure effects can be computed directly. For instance, the composition and structure components linked to the Market factor, $\hat{\Delta}_C^1$ and $\hat{\Delta}_S^1$, are obtained by $(\bar{X}_{a1}' - \bar{X}_{u1}') \hat{\beta}_{a1}$ and $\bar{X}_{u1}'(\hat{\beta}_{a1} - \hat{\beta}_{u1})$, respectively. The same applies to the components linked to other factors. Although the results from RIF-regression are path independent, they could be different while using another group as reference. For this reason, we substitute $\overline{RIF}_a^c$ with $\overline{RIF}_u^c = \hat{\alpha}_u + \bar{X}_a' \hat{\beta}_u$ as robustness checks. That is, we show the main results using NA as reference group and the robustness results using Europe as reference group.

IV.   Data

In the paper, North America (NA) includes United States and Canada, and Europe contains Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. To compare our results with Huang (2018), we choose the five factors based on $2X3$ sorts and 75 Size-B/M, Size-OP, and Size-Inv portfolios of North America and Europe respectively. The dataset is from Fama and French (2017), which can be downloaded from Kenneth R. French's personal website. The dataset includes the five factor returns and the monthly excess returns on the $5X5$ Size-B/M, Size-OP, and Size-Inv portfolios of North America and Europe, ranging from July 1990 to November 2017 (329 months).

We briefly describe as follows how the 75 portfolios of NA and Europe are constructed. At the end of June each year, stocks are allocated to five Size groups (Small to Big) using as breakpoints the 3rd, 7th, 13th, and 25th percentiles of the region's aggregate market capitalization. Stocks are allocated independently to five B/M groups (Low B/M to High B/M) by the quintile of B/M for the big stocks of the region. The intersections of the two sorts produce 25 Size-B/M portfolios. The 25 Size-Inv or Size-OP portfolios are constructed in the same way as in the Size-B/M portfolios except the second sort is on either profitability (robust minus weak) or investment (conservative minus aggressive). More details can be found in Fama and French (2017).

We report the summary statistics for the five factors and 75 portfolios studied in Table 1 and 2, respectively. We do not describe the statistics in detail. We summarize that the differences in the factor distributions and the correlations between factors make the decomposition interesting. The summary statistics in detail can be found in Huang (2018).

Table 1: Summary statistics for factor returns

(a) Mean and standard deviation

	North America					Europe					Difference				
	MKT	SMB	HML	RMW	CMA	MKT	SMB	HML	RMW	CMA	MKT	SMB	HML	RMW	CMA
Mean	0.67	0.17	0.20	0.34	0.26	0.51	0.07	0.34	0.40	0.21	0.16	0.10	-0.14	-0.06	0.05
SD	0.23	0.15	0.18	0.13	0.15	0.27	0.12	0.13	0.08	0.10	0.16	0.16	0.14	0.14	0.12

(b) Correlations of factor returns within and between NA and Europe

	North America					Europe					Between				
	Mkt	SMB	HML	RMW	CMA	MKT	SMB	HML	RMW	CMA	MKT	SMB	HML	RMW	CMA
MKT	1.00	0.20	-0.23	-0.37	-0.44	1.00	-0.17	0.18	-0.26	-0.30	0.80	-0.26	0.04	-0.22	-0.35
SMB	0.20	1.00	-0.10	-0.42	-0.14	-0.17	1.00	0.01	-0.05	0.02	-0.26	0.31	0.03	-0.03	-0.12
HML	-0.23	-0.10	1.00	0.38	0.78	0.18	0.01	1.00	-0.54	0.54	0.04	0.03	0.60	-0.15	0.52
RMW	-0.37	-0.42	0.38	1.00	0.35	-0.26	-0.05	-0.54	1.00	-0.18	-0.22	-0.03	-0.15	0.22	0.38
CMA	-0.44	-0.14	0.78	0.35	1.00	-0.30	0.02	0.54	-0.18	1.00	-0.35	-0.12	0.52	0.38	0.57

Note: The table shows the summary statistics for the factor returns in North America and Europe, respectively. Table (a) shows the means and the standard deviations of factor returns in excess of the one-month Treasury bill rate. Table (b) shows the correlations of factor returns within and between NA and Europe.

Table 2: Summary statistics for portfolio returns

(a) Mean

	North America					Europe				
	Small	2	3	4	Big	Small	2	3	4	Big
Low B/M	0.43	0.40	0.79	0.82	0.64	-0.08	0.29	0.34	0.49	0.34
2	0.60	0.62	0.68	0.70	0.66	0.37	0.49	0.56	0.53	0.53
3	0.91	0.79	0.78	0.81	0.63	0.45	0.55	0.54	0.59	0.57
4	0.88	0.80	0.78	0.77	0.65	0.59	0.71	0.54	0.55	0.64
High B/M	1.16	0.86	0.89	0.86	0.57	0.75	0.76	0.74	0.65	0.54
Low Inv	1.21	0.88	0.91	0.90	0.74	0.55	0.59	0.64	0.64	0.57
2	1.12	0.90	0.90	0.94	0.65	0.71	0.77	0.67	0.63	0.58
3	0.99	0.88	0.90	0.85	0.65	0.71	0.76	0.70	0.64	0.48
4	0.96	0.87	0.79	0.88	0.62	0.65	0.64	0.48	0.63	0.45
High Inv	0.54	0.36	0.54	0.51	0.55	0.16	0.37	0.30	0.39	0.45
Low OP	0.84	0.44	0.59	0.57	0.25	0.15	0.25	0.26	0.20	0.16
2	1.06	0.78	0.78	0.79	0.57	0.67	0.57	0.56	0.55	0.55
3	1.05	0.95	0.81	0.93	0.63	0.75	0.70	0.73	0.71	0.56
4	1.07	1.01	0.90	0.78	0.71	0.90	0.75	0.63	0.69	0.47
High OP	1.09	1.14	1.06	0.93	0.72	0.76	0.96	0.81	0.70	0.60

(b) Standard deviation

|	North America					Europe				
	Small	2	3	4	Big	Small	2	3	4	Big
Low B/M	7.96	7.31	6.88	6.44	4.53	5.49	5.63	5.71	5.39	4.84
2	6.82	6.49	5.70	5.06	4.10	5.27	5.25	5.23	4.99	4.77
3	6.13	5.47	5.02	4.57	4.21	4.95	5.02	5.14	5.01	5.21
4	5.39	4.92	4.72	4.58	4.12	4.84	5.06	5.18	5.35	5.42
High B/M	5.28	5.16	4.88	4.76	5.23	4.83	5.30	5.59	5.80	6.34
Low Inv	6.42	5.68	5.09	4.76	4.05	4.98	5.22	5.46	5.20	4.85
2	4.97	4.76	4.36	4.21	3.69	4.46	4.82	5.04	5.00	4.81
3	4.92	4.78	4.65	4.38	4.05	4.56	4.80	4.89	4.85	5.17
4	5.29	5.42	5.23	4.87	4.77	4.76	5.14	5.17	5.23	5.45
High Inv	6.80	6.92	7.26	6.64	5.82	5.69	5.74	5.94	6.07	5.35
Low OP	6.68	6.65	6.77	6.26	5.60	5.18	5.43	5.56	5.52	6.09
2	4.91	4.94	4.87	4.69	4.89	4.67	5.00	5.09	5.14	5.53
3	4.98	4.99	4.60	4.40	4.31	4.81	5.02	5.07	5.25	5.08
4	5.34	5.27	4.93	4.45	4.07	4.79	5.09	5.17	5.08	4.99
High OP	5.66	5.44	5.40	4.83	3.96	4.94	5.32	5.33	5.28	4.76

Note: The table shows the summary statistics for the 75 portfolios in North America and Europe, respectively. Table (a) shows means of monthly portfolio returns in excess of the one-month Treasury bill rate. Table (b) shows the standard deviations.

V.   Decomposition results

We first run unconditional quantile regression for each portfolio in North America and Europe then decompose the estimated quantile differences for each corresponding portfolio. Lastly, we average the results over all the portfolios. In sum, although not statistically significant due to the big standard errors, the decomposition results are economically significant. To show clearly the economic significance, we choose to not report the confidence intervals in the main text.[8]

Figure 1 shows the aggregate decomposition results. We obverse that the average overall differences across quantiles plummet in the lower quantiles and then climb from 20th through 70th quantiles and then decrease slowly after.For all quantiles, the composition effects are positive. This means that the differences in the distribution of factors between North America and Europe contribute positively to the quantile portfolio returns differences. More specifically, the aggregate composition effects increase in the lower quantiles while the overall difference decreases. The composition effects start to decrease slowly after reaching the maximum at about 25th quantile.

Figure 1: Aggregate decomposition effects
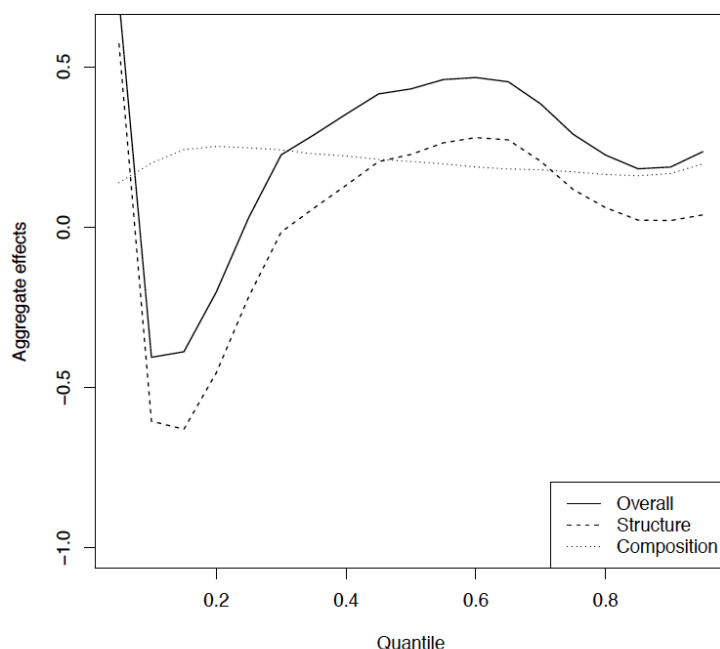
Notes: The figure plots the aggregate decomposition results across quantiles.

Also, the aggregate structure effects follow the pattern of the overall differences and play a significant role in explaining the differences in portfolio returns. The results seem to be inconsistent with Huang (2018) which says that the composition effects explain the most part of the differences and the structure effects play an insignificant role in aggregate. However, the detailed decomposition results below show that the structure effects linked to five factors together do not seem to playasignificant role. The seemingly significant aggregate structure effects are mostly contributed by the constant term.
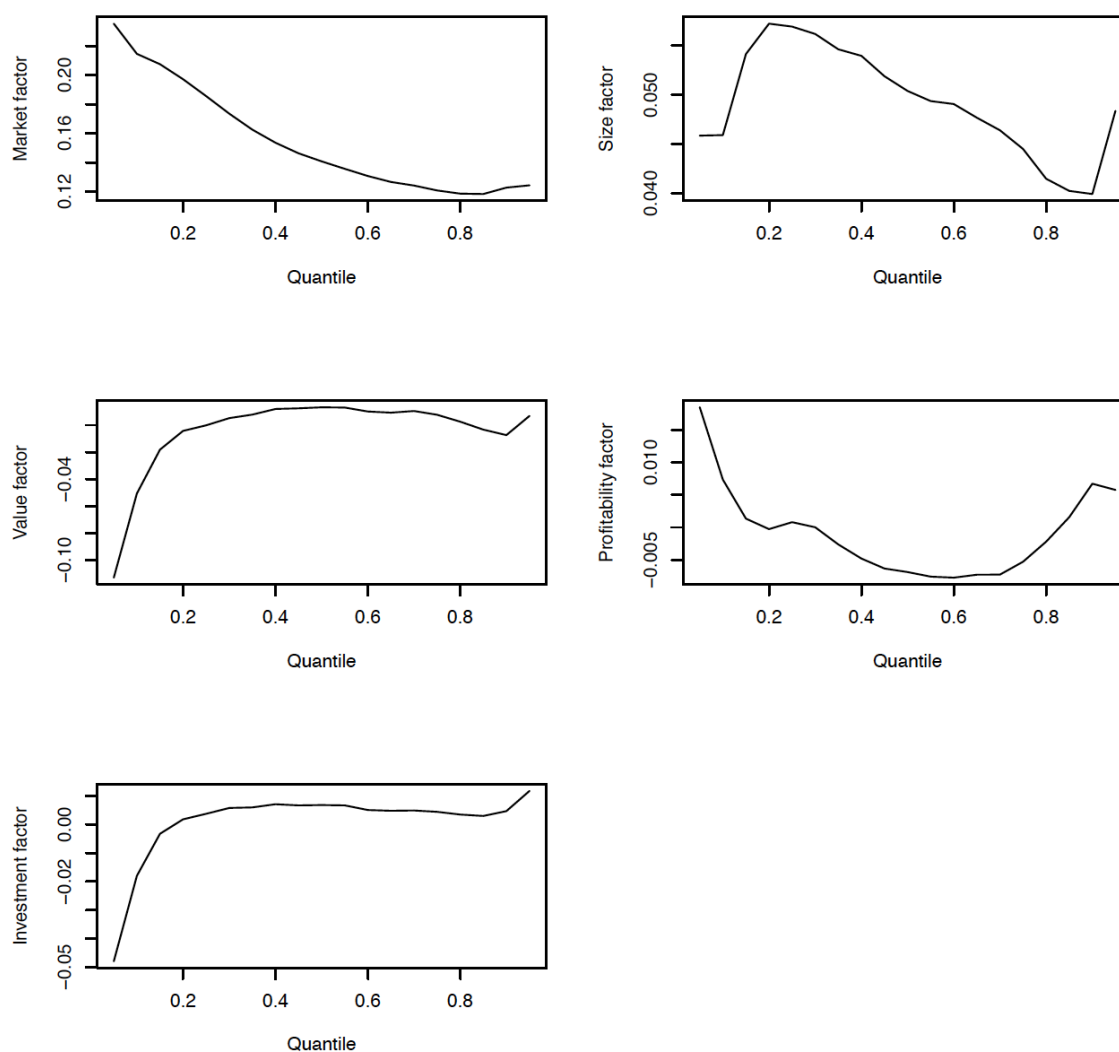
Figure 2 shows the detailed composition effects across quantiles.We observe obviously that the most of aggregate composition effects are contributed by the composition effect related to the market factor. The composition effect linked to market factor monotonically decreases with quantiles. This result could have important implications to investments and risk management and are worth further research. The left middle panel shows that the value factor contributes significantly to the composition effects in the lower quantiles. The distribution difference in other factors between North

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America and Europe do not seem to have economically significant effects on the overall quantile returns differences.

Figure 3 shows the detailed structure effects across quantiles. We observe that the very high and positive aggregate structure effects in the low quantiles are mostly explained by the differences in the constant terms. Also, except in the low quantiles the detailed structure effects do not seem to be economically significant.

Figure 2: Detailed composition effects

Notes: The figure plots the detailed composition effects across quantiles.

Figure 3: Detailed structure effects
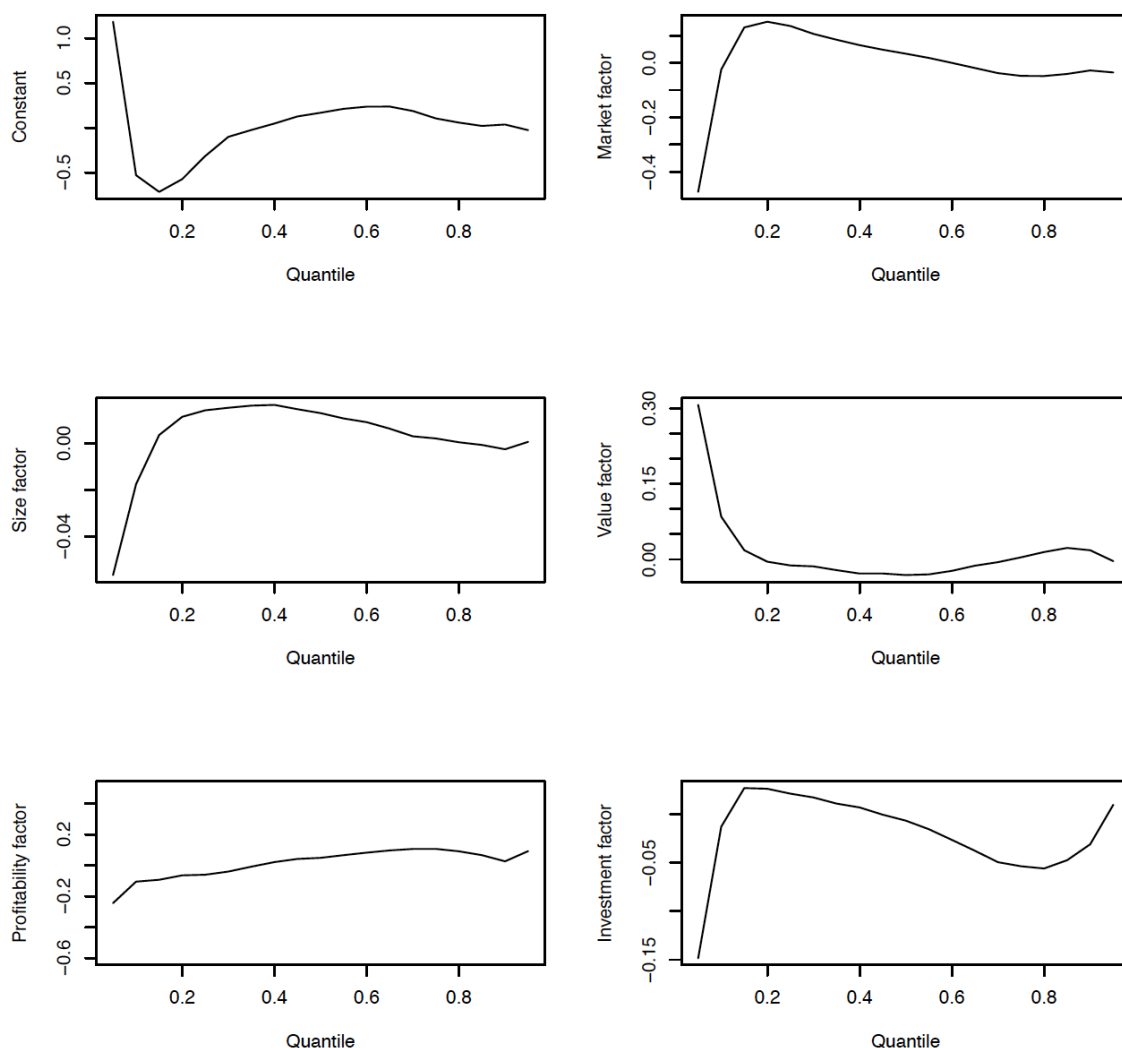
Notes: The figure plots detailed composition effects across quantiles.

5.1 Robustness

Although the decomposition results using RIF-regression are path independent, these results can be different by switching the reference group. In the main results shown above, we use NA as reference group. Here we show the results by using Europe as reference group. The results are shown in Figure 4-6.The aggregate and detailed decomposition effects using NA and Europe as reference groups across quantiles are similar except in the low quantiles.[9]That is, the decomposition results using RIF-regression are robust to switching the reference group.

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[9]Figures plot the differences between two results are not shown in the main text and are offered upon request.

Figure 4: Aggregate decomposition effects
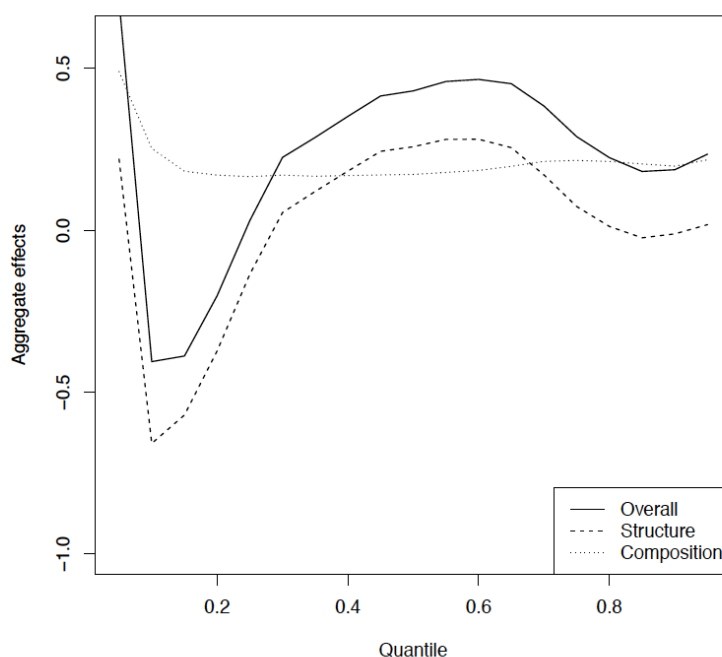
Notes: The figure plots the aggregate decomposition results across quantiles.

VI. Conclusion

The paper applies unconditional quantile regression to decompose the quantile difference in the portfolio returns between North America and Europe. The decomposition results are path dependent, which is complementary to the path dependent results from distribution regression in Huang (2018). We show that the composition effects are all positive across all quantiles.This is inconsistent with Huang (2018).Although the aggregate structure effects are economically significant, they are mostly contributed by the differences in the constant terms.That is, the differences in the factor risks together do not seem to play a significant role in explaining the quantile differences in portfolio returns. The composition effect linked to the market factor is economically large and contributes most to the overall different.These are consistent with Huang (2018).Also except in the low quantiles, the effects linked to the other factors do not seem to play a significant role in explaining the differences.
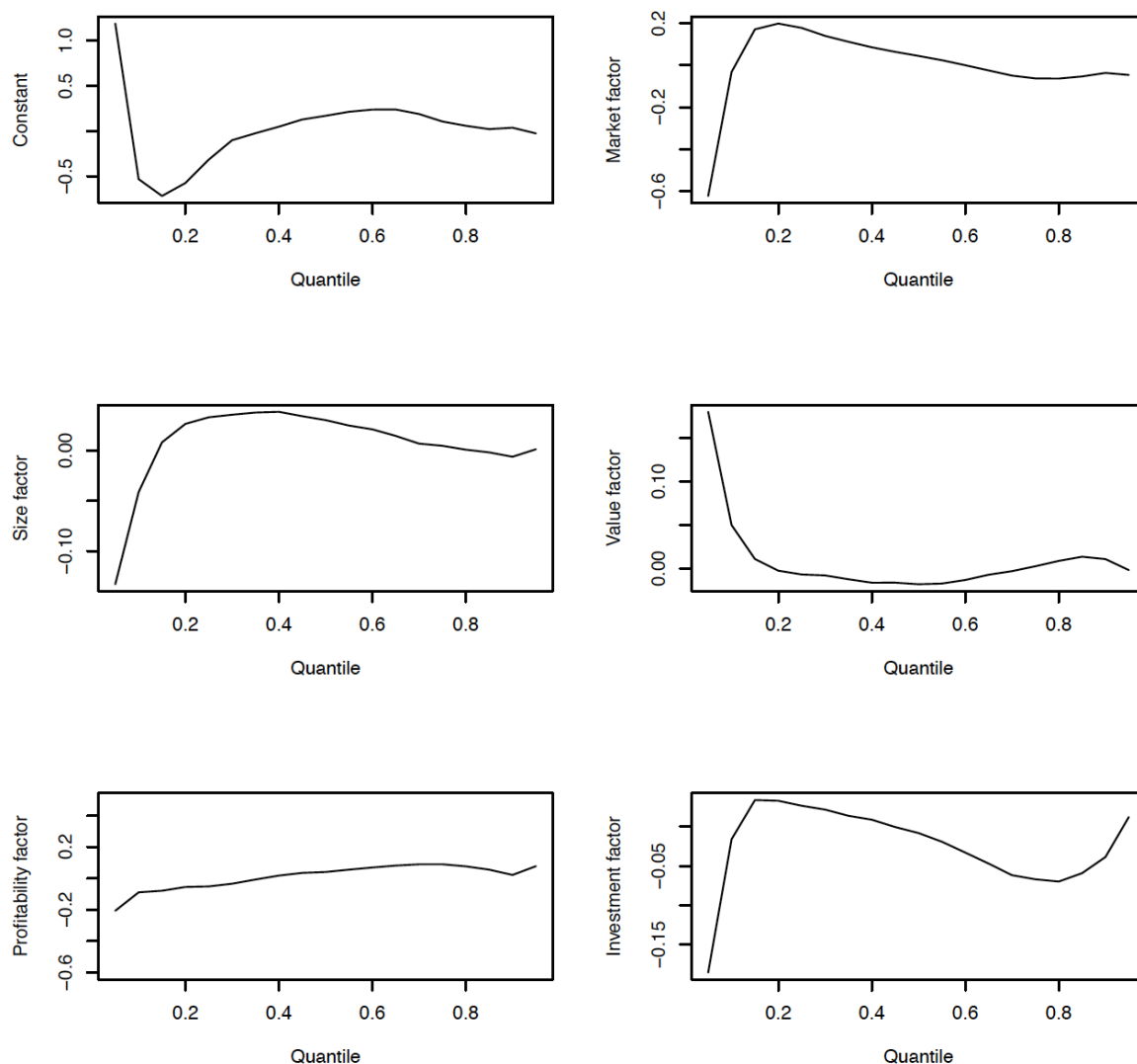
Figure 5: Detailed composition effects
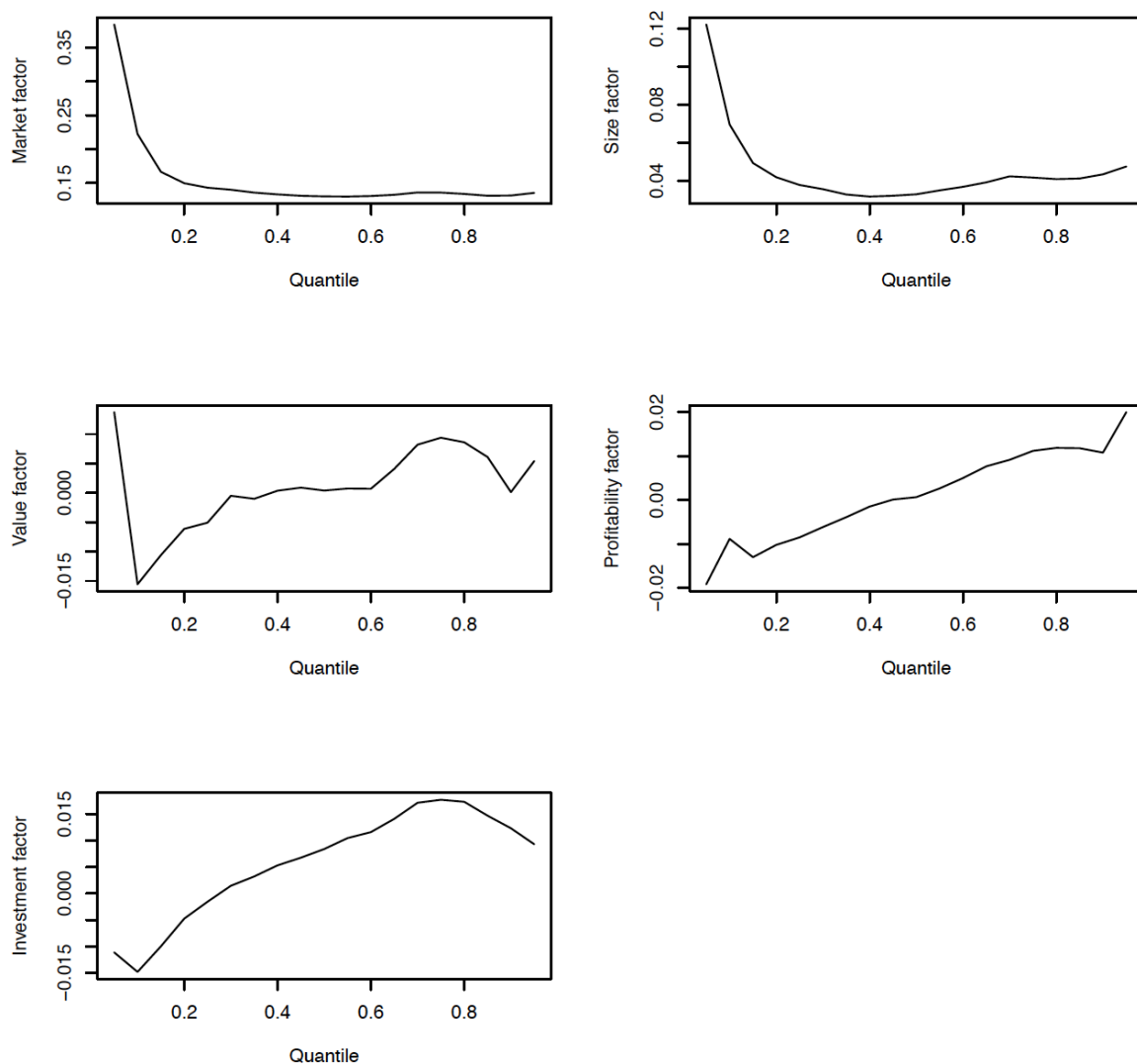
Notes: The figure plots the detailed composition effects across quantiles.

Figure 6: Detailed structure effects

Notes: The figure plots the detailed composition effects across quantiles.

REFERENCES

[1]   Aharoni, Gil, Bruce Grundy, and Qi Zeng. Stock returns and the Miller Modigliani valuationformula: Revisiting the Fama French analysis. Journal of Financial Economics 110.2 (2013),pp. 347-357.

[2]   Banz, Rolf W. The relationship between return and market value of common stocks.Journal of financial economics 9.1 (1981), pp. 3-18.

[3]   Basu, Sanjoy. The relationship between earnings' yield, market value and return for NYSEcommon stocks: Further evidence. Journal of Financial Economics 12.1 (1983), pp. 129-156.

[4]   Blinder, Alan S. Wage discrimination: reduced form and structural estimates. Journal ofHuman Resources (1973), pp. 436-455.

[5]   Borah, Bijan J and AnirbanBasu. Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence. Health Economics 22.9 (2013), pp. 1052-1070.

[6]   Breeden, Douglas T. An intertemporal asset pricing model with stochastic consumptionand investment opportunities. Journal of Financial Economics 7.3 (1979), pp. 265-296.

[7]   Breeden, Douglas T, Michael R Gibbons, and Robert H Litzenberger. Empirical tests ofthe consumption-oriented CAPM. The Journal of Finance 44.2 (1989), pp. 231-262.

[8]   Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly. Inference on counterfactualdistributions.Econometrica 81.6 (2013), pp. 2205-2268.

[9]   Cohen, Randolph B, Paul A Gompers, and TuomoVuolteenaho. Who underreacts to cashflow news? Evidence from trading between individuals and institutions. Journal of FinancialEconomics 66.2 (2002), pp. 409-462.

[10]   Fairfield, Patricia M, J Scott Whisenant, and Teri Lombardi Yohn. Accrued earnings andgrowth: Implications for future profitability and market mispricing. The Accounting Review78.1 (2003), pp. 353-371.

[11]   Fama, Eugene F and Kenneth R French. Common risk factors in the returns on stocks andbonds. Journal of Financial Economics 33.1 (1993), pp. 3-56.

[12]   Fama, Eugene F and Kenneth R French. Profitability, investment and average returns.Journal of Financial Economics 82.3 (2006), pp. 491-518.

[13]   Fama, Eugene F and Kenneth R French. Dissecting anomalies. The Journal of Finance63.4 (2008), pp. 1653-1678.

[14]   Fama, Eugene F and Kenneth R French. A five-factor asset pricing model. Journal ofFinancial Economics 116 (2015), pp. 1-22.

[15]   Fama, Eugene F and Kenneth R French. Dissecting anomalies with a five-factor model.The Review of Financial Studies 29.1 (2016), pp. 69-103.

[16]   Fama, Eugene F and Kenneth R French. International tests of a five-factor asset pricingmodel. Journal of Financial Economics 123.3 (2017), pp. 441-463.

[17]   Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux. Unconditional quantile regressions.Econometrica 77.3 (2009), pp. 953-973.

[18]   Foresi, Silverio and Franco Peracchi. The conditional distribution of excess returns: Anempirical analysis. Journal of the American Statistical Association 90.430 (1995), pp. 451-466.

[19]   Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. Decomposition methods in economics.Handbook of Labor Economics 4 (2011), pp. 1-102.

[20]   Haugen, Robert A and Nardin L Baker. Commonality in the determinants of expectedstock returns. Journal of Financial Economics 41.3 (1996), pp. 401-439.

[21]   Hou, Kewei, Chen Xue, and Lu Zhang. Digesting anomalies: An investment approach. TheReview of Financial Studies 28.3 (2015), pp. 650-705.

[22]   Huang, Weige. Decomposing Differences in Portfolio Returns Between North America and Europe. Working paper. 2018.

[23]   Lintner, John. The valuation of risk assets and the selection of risky investments in stockportfolios and capital budgets. The Review of Economics and Statistics (1965), pp. 13-37.

[24]   Maclean, Johanna Catherine, Douglas A Webber, and Joachim Marti. An application ofunconditional quantile regression to cigarette taxes. Journal of Policy Analysis and Management 33.1 (2014), pp. 188-210.

[25]   Novy-Marx, Robert. The other side of value: The gross profitability premium. Journal ofFinancial Economics 108.1 (2013), pp. 1-28.

[26]   Oaxaca, Ronald. Male-female wage differentials in urban labor markets. InternationalEconomic Review (1973), pp. 693-709.

[27]   Reinganum, Marc R. A new empirical perspective on the CAPM. Journal of Financial andQuantitative Analysis 16.4 (1981), pp. 439-462.

[28]   Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein. Persuasive evidence of market inefficiency. The Journal of Portfolio Management 11.3 (1985), pp. 9-16.

[29]   Sharpe, William F. Capital asset prices: A theory of market equilibrium under conditionsof risk. The Journal of Finance 19.3 (1964), pp. 425-442.

[30]   Titman, Sheridan, KC John Wei, and FeixueXie. Capital investments and stock returns. Journal of Financial and Quantitative Analysis 39.4 (2004), pp. 677-700.