# Asset Pricing - Empirical Application 1

# Factorial Model and Risk Premium Decomposition - APT

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## Introduction

Focusing on recent data from the French equity market, we want to better comprehend how the market prices systemic, non-diversifiable risk embedded in the risk premium of stocks, i.e. any expected compensation beyond the risk-free return. We base our analysis on a linear decomposition of said premium on different *factors* of risk in the spirit of the Arbitrage Pricing Theory (APT) pioneered by Ross [1976]. Unlike the CAPM model which considers a unique risk premium in the market, the Ross model gives a more detailed description of the pricing of aggregate risk by decomposing the contributions of different sources of risk. Here, a risky portfolio of $j$ stocks[1] is compensated with $k$ risk premia associated with the $k$ *common factors* that the portfolio is exposed to.

## 1 Data

### 1.1 French stock market data

We decided to build a case study of the French market because it is a liquid and matured market, central in Europe. In the case of this analysis, we had trouble getting the data needed to perform it for other countries[2] and the fact that France has more publicly available data helped us choose it as our market of study.

We built a portfolio with 30 French stocks that we got from Yahoo Finance. For simplicity, the synthetic portfolio is composed of one stock of each company and its composition does not change during the period studied. Table 1 shows the companies that we used to create this portfolio, they are all publicly traded companies in France since the early 2000's in Euronext Paris. Importantly, we tried to have a certain diversity in the sectors

[1] Let $j \in \{1, ..., J\}$ with $J$ sufficiently large so that all idiosyncratic risk can be fully diversified. We better explain the difference between idiosyncratic and aggregate in the context of the Ross model in Section 1.1

[2] Initially we thought about using data from the German market but we couldn't for instance find data for their inflation-linked bond yield that we use as an endogenous factor in Section 2.1.2

represented to be able to capture some diversification to risk even if the portfolio is too small and we do not reweight it. However, because we try to implement a version of the Fama and French [1992] factor analysis, we restrain ourselves from choosing financial companies as the authors do due to their high leverage. Other than these two conditions, the choice of the companies was mainly restricted to data availability on public 'long' series on firm-level data, notably on market capitalization and book-to-market ratio to be able to incorporate the Fama and French [1992] factors to our analysis.

describe frequency of data

Because we are interested in the underlying determinants of the risk premia, and due to data availability issues, we decided to have a broad analysis with monthly data for our selection of

| Company Name | Ticker | Industry |
|---|---|---|
| Accor | AC.PA | Hospitality |
| Air Liquide | AI.PA | Industrial Gases |
| Air France-KLM | AF.PA | Airlines |
| Airbus | AIR.PA | Aerospace |
| Biomerieux | BIM.PA | Biotechnology |
| BIC | BB.PA | Consumer Goods |
| Bouygues | EN.PA | Construction |
| Capgemini | CAP.PA | Information Technology |
| Carrefour | CA.PA | Retail |
| Casino | CO.PA | Retail |
| Dassault Aviation | AM.PA | Aerospace |
| Danone | BN.PA | Food and Beverage |
| Hermes International | RMS.PA | Fashion and Luxury |
| JCDecaux | DEC.PA | Advertising |
| Kering | KER.PA | Fashion and Luxury |
| L'Oreal | OR.PA | Cosmetics |
| LVMH | MC.PA | Fashion and Luxury |
| Michelin | ML.PA | Automotive |
| Nexans | NEX.PA | Electrical Equipment |
| Orange | ORA.PA | Telecommunications |
| Renault | RNO.PA | Automotive |
| Saint-Gobain | SGO.PA | Manufacturing |
| Sanofi | SAN.PA | Pharmaceuticals |
| Sodexo | SW.PA | Food Services |
| TF1 | TFI.PA | Broadcasting |
| Thales | HO.PA | Aerospace and Defense |
| TotalEnergies | TTE.PA | Energy |
| Ubisoft | UBI.PA | Video Games |
| Vinci | DG.PA | Construction |
| Vivendi | VIV.PA | Entertainment |

Table 1: Synthetic portfolio: Companies, Tickers, and Industries

## 1.2 Data description and sources

The other series that we use are the following and its sources, how they are used in the context of the analysis is described in subsequent sections.

- As a proxy for the free rate of the market we consider two measures:
  - The yield of short-term OAT, i.e. French treasuries taken from Banque de France's website. As for most developed, stable countries, short-term sovereign bonds are taken as the risk-free asset as Governments are supposed to be more solvent than other agents in the economy, after all, they decide their income and could seize resources via taxes to meet their obligations.
  - The spot yield curve spot rate, for 3-month maturity of all government bonds rated triple A in the Euro Area, retrieved from the ECB webpage. On top of the fact that this is a measure for short-term sovereign bonds, we consider this to be a relevant proxy for the French market due to the strong integration within the European capital market. If an investor decides that the French market becomes risky, she can easily move her investments to another European capital market that looks safer.
- To get the market rate, we use the return of the main index of the country, the CAC40 also taken from Yahoo Finance as for the components of our synthetic portfolio. In hindsight, we are not sure of the pertinence of comparing our portfolio to this index. While the composition of our portfolio is not the same as the CAC40[3], due to the data availability issues we've been mentioning, we see that our choices are heavily biased towards 'big name' companies that are those belonging to the index.
- We got the series of the exchange rate between the Euro and the US dollar from Yahoo Finance. It is read as the amount of USD needed to get an euro.
- The GDP series is taken from the ECB webpage. It is available at a quarterly frequency and is available at market prices.
- The harmonized headline inflation rate is taken from the INSEE webpage.
- For the market inflation expectation in a 10-year horizon, we use the break-even inflation rate published by Agence France Trésor online. Sadly, data is only available from 2013.
- For the implementation of the two additional Fama and French [1992] factors, we took different routes
  - We found the estimation of the factors published by K. French in his online Data Library that are constantly updated. Their estimations start in the 1990s and are made for different markets using the comprehensive CRSP dataset that is not freely available. He has an estimation for the European market that we downloaded to use but it is not clear which stocks are used to replicate their portfolio.
  - To try to build these estimations ourselves for our portfolio meaning that a minima we need data on the market capitalization of each company during the time frame studied and its *book*. This information is hardly available without having access to platforms like Bloomberg or CRSP. The best information that we could find comes from this website that publishes the market capitalization and the price-to-book (the inverse of the book-to-market ratio) annual series for several stocks. The data is however cannot be directly downloaded from the site so we scrap it to get the series (see Code

[3] Not all the stocks we chose are necessarily part of the CAC40 at every period studied, and the CAC40 is a weighted index that evolves over time.

Appendix A). Our biggest fear with this source is that it is not clear at all where the information comes from even if they mention several quality data providers as their partners. Since it is the only source that resembles what is needed for this part we used it but we are not confident on it.

# 2 Empirical strategy and implementation

We implement a minimal approach to Ross [1976], namely using fewer factors than in Chen et al. [1986]. We include both exogeneous and endogenous macroeconomic risk factors as well as an approximation to implement Fama and French [1993] three-factor model which used stock specific data.

Let the return $R_j$ of the $j$-th component of her portfolio can be described by the following expression $\forall j \in \{1, ..., N\}$:

$$R_j = \mathbb{E}[R_j] + \underbrace{\sum_{k=1}^{K} \beta_{j,k} f_k}_{\text{Systemic risk}} + \overbrace{u_j}^{\text{Idiosyncratic risk}} \tag{1}$$

Where $\mathbb{E}[R_j]$ is the expected return of asset $j$. The sources of risk are two-fold. The investor faces centered idiosyncratic risks $u_j$, $\mathbb{E}[u_j] = 0$ that are assumed to be completely diversiable with a portfolio "large enough" $(N$ big) because they are independent of each other $u_j \perp\!\!\!\perp u_{j'} \forall j \neq j'$, and uncorrelated with aggregate risk $corr(u_j, f_k) = 0, \forall j, k$ which is a required assumption to perform the estimations that will follow. She also faces $k$ different sources of aggregate risk, modeled by the linear combination of $f_k$ centered *shocks* that influence all $R_j$ with a sensitivity $\beta_{jk}$. By definition, these risks cannot be diversified because they affect the returns of all asset and thus has to be compensated which is the focal point of our study.

## 2.1 Identify the risk factors

### 2.1.1 Exogeneous factors

### 2.1.2 Endogeneous factors

### 2.1.3 French-Fama factors

## 2.2 Estimate the $\beta_k$ coefficients from the factorial model

## 2.3 Estimate the $\lambda_k$ parameters from the multibeta relationship

## 2.4 Test the validity of the multibeta relationship

# Conslusion

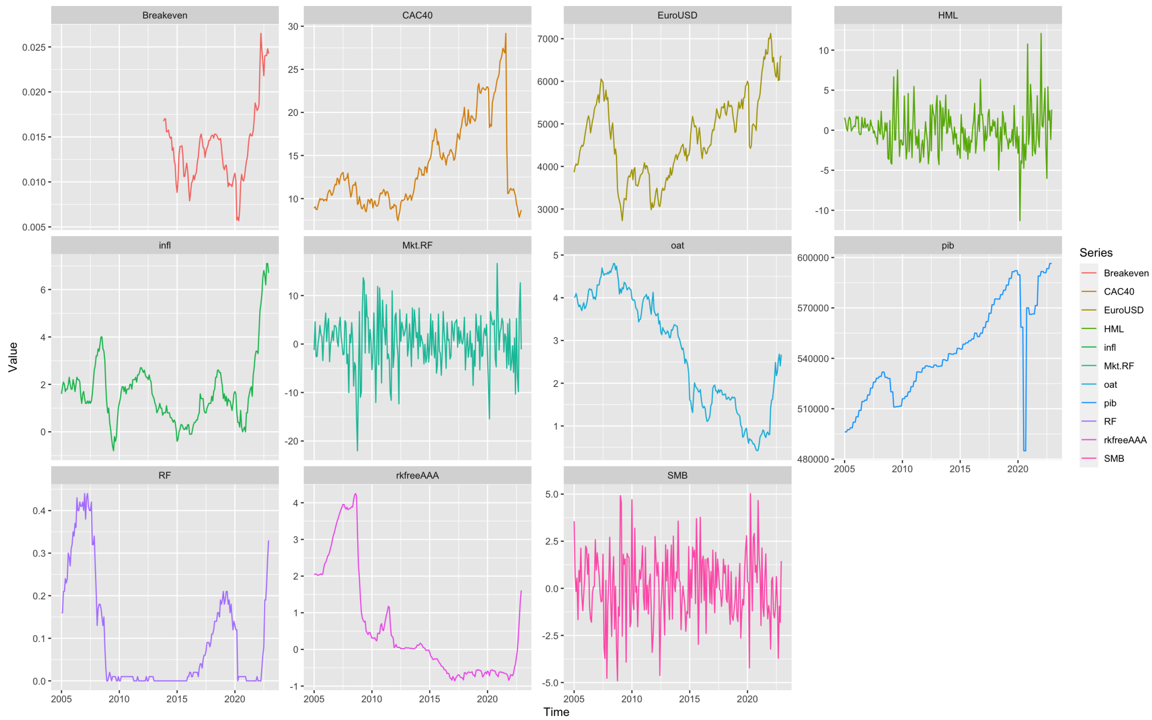


Figure 1: ML algorithms and discrimination

# Appendix A Code - Data gathering and cleaning

```python
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
AP1 - Data gathering and Data Cleaning

Scrapping - Firm level data for French and Fama factors
Use Yahoo Finance API to get the financial data for all the stocks
Use Eurostat API to get the macro data
Two data sets (French-Fama factors and long term inflation expectation) are found online and have been downloaded in CSV file beforehang

Merge and clean the dataset

@author: nataliacardenasf
"""

import pandas as pd
import numpy as np
import os

import requests
from bs4 import BeautifulSoup

```

```python
#import pandas_datareader.data as web
import yfinance as yf
#from eurostatapiclient import EurostatAPIClient
import datetime


os.chdir('/Users/nataliacardenasf/Documents/GitHub/PROJECTS_AP_FE/AP 1')

company_names_lower = [
    'air-liquide', 'airbus', 'bouygues', 'capgemini', 'carrefour', 'casino-guichard-perrachon', 'vivendi',
    'kering', 'l-oreal', 'lvmh', 'michelin', 'orange', 'renault', 'sanofi', 'thales',
    'totalenergies', 'vinci', 'compagnie-de-saint-gobain', 'ubisoft', 'tf1', 'danone',
    'dassault-aviation', 'air-france-klm', 'accor', 'bic', 'hermes-international',
    'jcdecaux', 'nexans', 'sodexo', 'biomerieux', "CAC40", "EuroUSD"]

tickers = [
    'AI.PA', 'AIR.PA', 'EN.PA', 'CAP.PA', 'CA.PA', 'CO.PA', 'VIV.PA', 'KER.PA', 'OR.PA', 'MC.PA',
    'ML.PA', 'ORA.PA', 'RNO.PA', 'SAN.PA', 'HO.PA', 'TTE.PA', 'DG.PA', 'SGO.PA', 'UBI.PA', 'TFI.PA',
    'BN.PA', 'AM.PA', 'AF.PA', 'AC.PA', 'BB.PA', 'RMS.PA', 'DEC.PA', 'NEX.PA', 'SW.PA', 'BIM.PA', "^FCHI", 'EURUSD=X']



#%% Scrap firm level data for French and Fama factors
# List of companies' URLs
mktcap_urls = ['https://companiesmarketcap.com/'+ x+'/marketcap/' for x in company_names_lower[:-2]]
pricebook_urls = ['https://companiesmarketcap.com/'+ x+'/pb-ratio/' for x in company_names_lower[:-2]]


# Scrapping functions
def scrape_market_cap(url, company_name):
    response = requests.get(url)
    if response.status_code == 200:
        soup = BeautifulSoup(response.content, 'html.parser')
        table_body = soup.find('table', class_='table').find('tbody')
        if table_body:
            data = []
            rows = table_body.find_all('tr')
            for row in rows:
                cols = row.find_all('td')
                if len(cols) >= 2:
                    year = cols[0].text.strip()
                    market_cap = cols[1].text.strip()
```

```
                    #variation = cols[2].text.strip()
                    data.append({'Year': year, 'MarketCap': market_cap, 'Company': company_name})
            return pd.DataFrame(data)
    return None

def scrape_price_book(url, company_name):
    response = requests.get(url)
    if response.status_code == 200:
        soup = BeautifulSoup(response.content, 'html.parser')
        table_body = soup.find('table', class_='table').find('tbody')
        if table_body:
            data = []
            rows = table_body.find_all('tr')
            for row in rows:
                cols = row.find_all('td')
                if len(cols) >= 2:
                    year = cols[0].text.strip()
                    pricebook = cols[1].text.strip()
                    #variation = cols[2].text.strip()
                    data.append({'Year': year, 'PriceBook': pricebook, 'Company': company_name})
            return pd.DataFrame(data)
    return None


# Scraping market cap data
dfmktcap = pd.DataFrame()
for url, company in zip(mktcap_urls, company_names_lower[:-2]):
    data = scrape_market_cap(url, company)
    if data is not None:
        dfmktcap = pd.concat([dfmktcap, data])

#Scap price book
dfpricebook = pd.DataFrame()
for url, company in zip(pricebook_urls, company_names_lower[:-2]):
    data = scrape_price_book(url, company)
    if data is not None:
        dfpricebook = pd.concat([dfpricebook, data])

#indexes
dfmktcap['Year'] = pd.to_datetime(dfmktcap['Year'])
dfmktcap['Year'] = pd.DatetimeIndex(dfmktcap['Year']).year

dfpricebook['Year'] = pd.to_datetime(dfpricebook['Year'])
dfpricebook['Year'] = pd.DatetimeIndex(dfpricebook['Year']).year


```

```python
##Merge datasets
final_firm = dfmktcap.copy()
final_firm = final_firm.merge(dfpricebook, how='outer', on=['Year', 'Company'])


del dfmktcap, dfpricebook, mktcap_urls, pricebook_urls, url, data, company


missing = final_firm[final_firm.isna().any(axis=1)]
missing = missing.sort_values(by=['Year'])
missing = missing.reset_index()
#have both data points for all firms for 2010-2022
# in 09 only missing data is from BIC, Carrefour, Ubisolft, AirFrance

#remove 2023
final_firm = final_firm[final_firm.Year != 2023]

#Get book to market ratio = inverse of price-book ratio
final_firm['PriceBook'] = pd.to_numeric(final_firm['PriceBook'], errors='coerce')
final_firm['PriceBook'].replace('nan', np.nan, inplace=True)
final_firm['BookMarket']  = final_firm['PriceBook'].apply(lambda x: x ** -1 if not pd.isnull(x
    ) else np.nan)

#Clean MarketCap
final_firm['MarketCap'] = (final_firm['MarketCap'].replace({'\$': '', ' B': ''}, regex=True).
    astype(float) * 1_000)  # Clear the letters, convert to float and scale to millions

#Date format
final_firm['Year'] = pd.to_datetime(final_firm['Year'], format='%Y')

#====Get monthly data
monthly_data = pd.DataFrame()
# Repeat the yearly data for each month and each firm
for index, row in final_firm.iterrows():
    firm_data = pd.DataFrame()
    monthly_year = pd.date_range(start=row['Year'], periods=12, freq='MS')
    firm_data['Date'] = monthly_year
    firm_data['Company'] = row['Company']
    firm_data['MarketCap'] = row['MarketCap']
    firm_data['BookMarket'] = row['BookMarket']
    firm_data['PriceBook'] = row['PriceBook']
    monthly_data = pd.concat([monthly_data, firm_data])

del index, monthly_year, row, firm_data

firms_year = final_firm.copy()
firms_month = monthly_data.copy()

```

```python
del final_firm, monthly_data, missing

#%%Get return data with Yahoo finance

start = datetime.datetime(2002, 1, 1)
end = datetime.datetime(2022, 12, 31)

#Get all data
data = yf.download(tickers, start=start,
                   end=end)

#Focus on adjusted closed values only
adjclose=data['Adj Close']
adjclose = adjclose.set_axis(company_names_lower, axis=1)

#Use monthly data: mean of the months value
adjclose = adjclose.resample('1M').mean(numeric_only=True)
adjclose_y = adjclose.resample('1Y').mean(numeric_only=True)

## extract CAC40 and exchange rate
cac_xrate_month = adjclose.loc[:, ["CAC40", "EuroUSD"]]
cac_xrate_year = adjclose_y.loc[:, ["CAC40", "EuroUSD"]]
adjclose = adjclose.drop(columns=["CAC40", "EuroUSD"])
adjclose_y = adjclose_y.drop(columns=["CAC40", "EuroUSD"])

#Reshape
prices_monthly = pd.melt(adjclose, value_vars=company_names_lower[0:-2], ignore_index=False)
prices_yearly = pd.melt(adjclose_y, value_vars=company_names_lower[0:-2], ignore_index=False)


del data, adjclose, adjclose_y, start, end

#%% Endogeneous factor: long term inflation expectation from external file

#upload the Agence France Tresor data
pi_endo= pd.read_excel('2023_11_01_rend_tit_ref_oatei.xls', skiprows=[0,1,2,3,4], usecols
    =[0,3])
pi_endo.columns = ['Date', "Breakeven"]

pi_endo["Date"] = pd.to_datetime(pi_endo["Date"])
pi_endo= pi_endo.set_index(pi_endo["Date"])
pi_endo.drop(columns=['Date'])

#get monthly data
piendo_month = pi_endo.resample('1M').mean(numeric_only=True)

#get yearly data
piendo_year = pi_endo.resample('1Y').mean(numeric_only=True)
```

```python

del pi_endo

#%% French and Fama - their data

df = pd.read_csv('Europe_3_Factors.csv',skiprows=[0,1,2])

#montly data, need to fix dates
frenchfama_month = df.iloc[:399,:]

frenchfama_month['Unnamed: 0'] = frenchfama_month['Unnamed: 0'].astype(str)  # Convert to string for manipulation
frenchfama_month['Year'] = frenchfama_month['Unnamed: 0'].str[:4]  # Extract year from the encoded date
frenchfama_month['Month'] = frenchfama_month['Unnamed: 0'].str[4:]  # Extract month from the encoded date
frenchfama_month['Date'] = pd.to_datetime(dict(year=frenchfama_month['Year'], month=frenchfama_month['Month'], day=1))
frenchfama_month.drop(['Year', 'Month', 'Unnamed: 0'], axis=1, inplace=True)
frenchfama_month = frenchfama_month.set_index(frenchfama_month['Date'])
frenchfama_month = frenchfama_month.drop(columns=["Date"])
frenchfama_month = frenchfama_month.loc['2002-01-01':]
frenchfama_month = frenchfama_month.astype(float)


#yearly data
frenchfama_year = df.iloc[402:,:]
frenchfama_year["Unnamed: 0"] = pd.to_datetime(frenchfama_year['Unnamed: 0'])
frenchfama_year.rename(columns={"Unnamed: 0":'Date'}, inplace=True)
frenchfama_year = frenchfama_year.set_index(frenchfama_year['Date'])
frenchfama_year = frenchfama_year.drop(columns=["Date"])
frenchfama_year = frenchfama_year.loc['2002-01-01':]
frenchfama_year = frenchfama_year.astype(float)

del df


#%% Macro data
#APIs didn't work as planned

## PIB Q
pib = pd.read_csv("ECB_PIB.csv")
pib.columns = ['Date', 'Q', 'pib']
pib['Date'] = pd.to_datetime(pib['Date'])
pib = pib.drop(columns=['Q'])
pib = pib.set_index(pib['Date'])
pib = pib.loc['2002-01-01':]
pib = pib.drop(columns=['Date'])
```

```

#monthly
pib_monthly = pib.resample('MS').ffill()
#yearly
pib_year = pib.resample('1Y').last()

del pib

##risk free AAA
rkfreeAAA = pd.read_csv('ECB_yield.csv')
rkfreeAAA.columns=['Date', "time" ,"rkfreeAAA"]
rkfreeAAA['Date'] = pd.to_datetime(rkfreeAAA['Date'])
rkfreeAAA = rkfreeAAA.set_index(rkfreeAAA['Date'])
rkfreeAAA = rkfreeAAA.drop(columns=['time', "Date"])

rkfreeAAA_monthly = rkfreeAAA.resample("1M").mean(numeric_only=True)
rkfreeAAA_year = rkfreeAAA.resample("1Y").mean(numeric_only=True)

del rkfreeAAA

##HICP
pi_month = pd.read_csv("HICP.csv", sep=';', encoding = 'latin1',skiprows=[0,1,2,3], usecols=[0,1], header=None)
pi_month.columns= ['Date', "infl"]
pi_month["Date"] = pd.to_datetime(pi_month['Date'], format = "%Y-%m")
pi_month=pi_month.set_index(pi_month["Date"])
pi_month = pi_month.drop(columns=['Date'])

#yearly
pi_year = pi_month.resample("1Y").mean(numeric_only=True)


##OAT
oat = pd.read_csv('OAT.csv', sep=';', skiprows=[0,1,2,3,4,5], usecols=[0,5], header=None)
oat.columns = ['Date', 'oat']
oat['Date'] = pd.to_datetime(oat["Date"])
oat = oat.set_index(oat["Date"])
oat = oat.drop(columns=["Date"])
oat = oat.loc["2002-01-01":]

oat['oat'] = oat['oat'].replace("-", np.nan)
oat['oat'] = oat['oat'].str.replace(',', '.').astype(float)

oat_month = oat.resample('M').mean(numeric_only=True)
oat_year = oat.resample('1Y').mean(numeric_only=True)

del oat

```

```
#%% Merge the dataframes

#===MONTHLY
#macro stuff, only date index matter
monthly = pd.concat([cac_xrate_month, frenchfama_month, oat_month, pi_month, pib_monthly,
    piendo_month, rkfreeAAA_monthly], axis=1)
monthly= monthly.resample('M').last() #some tables encoded end of month, others on the 1st

monthly.to_csv('Monthly_series.csv')


#firm specific data
firms_month['Date'] = firms_month['Date'] + pd.offsets.MonthEnd(0) #all other df have eomonth
    date
firms_month = firms_month.set_index(['Date'])
firms_month = firms_month.set_index('Company', append=True)

prices_monthly.columns = ['Company', 'value']
prices_monthly.set_index('Company', append=True)

monthly_stock = pd.merge(prices_monthly.reset_index(), firms_month.reset_index(), on =["Date",
     "Company"], how='outer').set_index(["Date", "Company"])
monthly_stock.to_csv("Firm_monthly.csv")

#merge the two
merged_monthly = pd.merge(monthly, monthly_stock, left_index=True, right_index=True, how='
    right')

#Export df in csv
merged_monthly.to_csv("DATA_month.csv")



#=== YEARLY
yearly = pd.concat([cac_xrate_year, frenchfama_year, oat_year, pi_year, pib_year, piendo_year,
     rkfreeAAA_year], axis=1)
yearly = yearly.resample('Y').last()

yearly.to_csv('Yearly_series.csv')

# =============================================================================
# #firm specific
# firms_year.rename(columns={"Year":'Date'}, inplace=True)
# firms_year['Date'] = firms_year['Date'] + pd.offsets.MonthEnd(0)
# firms_year = firms_year.set_index(['Date'])
# firms_year = firms_year.set_index('Company', append=True)
#
```

```
# prices_yearly.columns = ['Company', 'value']
# prices_yearly = prices_yearly.set_index('Company', append=True)
#
# yearly_stock = pd.merge(prices_yearly.reset_index(), firms_year.reset_index(), on =["Date",
    "Company"], how='outer').set_index(["Date", "Company"])
# =============================================================================

#yearly_stock = monthly_stock.groupby('Company').resample('Y').mean()

monthly_data_reset = monthly_stock.reset_index()
yearly_stock = monthly_data_reset.groupby('Company').resample('Y', on='Date').mean()
yearly_stock = yearly_stock.set_index(["Date", "Company"])

yearly_stock.to_csv("Firm_yearly.csv")


#merge the two
merged_year = pd.merge(yearly, yearly_stock, left_index=True, right_index=True, how='right')

merged_year.to_csv("DATA_yearly.csv")
```

# Appendix B Code - Analysis

```
#%% AP 1
#%% ncardenasfrias

pacman::p_load(data.table, tidyverse, gplots, xts, stargazer, plm)

setwd('/Users/nataliacardenasf/Documents/GitHub/PROJECTS_AP_FE/AP 1')

df <- fread("DATA_month.csv")
as.data.table(df)


## Identify the risk factors
#Need to remove the predicatable part to the endogeneous and exogeneous series

  #upload the monthly data with the yearly factors  and transform into a list of TS
data = read.csv('Monthly_series.csv')
data$Date <- as.Date(data$Date)

# Filter rows between 2005 and 2022
filtered_data <- data %>%
  filter(Date >= as.Date("2005-01-01") & Date <= as.Date("2022-12-31"))

time_series_cols <- filtered_data %>%
  select(-Date)

```

```
time_series_list <- lapply(time_series_cols, function(col) {
  ts_values <- ts(col, start = c(year(min(filtered_data$Date)), month(min(filtered_data$Date))), frequency = 12)
  return(ts_values)
})

names(time_series_list) <- names(time_series_cols)




## Estimate the beta coefficients


## Estimate the lamdas


#Test the validity of the multi-beta relationship
```

# 3 Data and Framework

## 3.1 German Stock Market

We decided to consider the German stock market for this analysis because it is a major liquid stock market in Europe. It is also the biggest economy in the Europe, with mayor

## 3.2 Estimation of the Factors

We need to choose what factors we are going to consider to generate risk premia that affect the return for the investor. In this section we examine the role of different types of factors (i) exogenous, (ii) endogeneous and we examine more closely the three-factor model proposed by Fama and French [1993] in (iii).

## 3.3 Exogeneous Factors

These are risk factors that are supposed to be orthogonal to the portfolio itself. In particular, it is interesting to consider the role of

## 3.4 Endogeneous Factors

## 3.5 French-Fama Factors

Fama and French [1993] can be seen as an extension of the CAPM model. The authors show that the variation of the returns of an asset can be explained not only by the exposure to market risk as in the CAPM represented by the difference of the market return and the risk-free rate $[R_M - R_f]$, but also by a size and value premium in the following model.

$$R_j = \alpha_j + R_f + \beta_{m,j}[R_M - R_f] + \beta_S SMB + \beta_V HML + \varepsilon_j \tag{2}$$

The size premium refers to the observation that stocks with small market capitalizations tend to outperform stocks with larger ones and it is captured by the factor SMB, *small minus big*. It is computed as the difference in average returns of the $30\%$ stocks with the smallest market capitalization and the average returns of the $30\%$ stocks associated with the firms with the largest market capitalization. The value premium refers to the outperformance of "value stocks" i.e. those that have high book-to-market (B/M) and it is represented by the difference in an average return of the $50\%$ of stocks with the highest $B/M$ ratio (value stocks) and the $50\%$ with lowest $B/M$ ratio (growth stocks).

# 4 Estimation of the exposure

# 5 Estimation of the market price of risk(s)

Consider a series of returns for different stock prices of at least 30 over a given period of time and frequency. The goal is to estimate rk premium by choosing a relevant so-called risk-free asset obtained as the return of treasury bond with relevant maturity

Develop econometric analysis which provides the multi-beta relationship 1. Identify the series for the risk factors (endo and exo) and justify choices + including 2 factors proposed by French and Fama 2. Estimate beta coeds or different stocks with relevant linear regression 3. Estimate market price of different sources of risk retained in analysis with appropriate linear reg

Comment the results from a financial point of view: are the estimated exposures of the different stocks to the different factors in line with expectations

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