The financialisation-offshoring nexus and the capital accumulation of US non-financial firms

Final Report
Heterodox Econometrics and quantitative methods

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Heterodox Econometrics and quantitative methods
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23rd January 2020

Abstract

With this report I seek to examine how firms in industrialised economies are able to sustain their profitability while at the same time cutting back real investment and increasing financial payouts to shareholders. Thereto I will examine the relation of financialisation to the sphere of production, especially the internationalization of the production process, and its effect on capital accumulation. I do so by trying to replicate what Tristan Auvray and Joel Rabinovich have done in their paper “The financialisation–offshoring nexus and the capital accumulation of US non-financial firms”, which was published 2019 in the Cambridge Journal of Economics. As I did not enjoy an education in econometrics nor in advanced statistics prior to the course, it was really difficult for me to succeed in the replication of the econometrics. This report should thus rather be read as a mirror of my learning process, trying to understand what we engaged with in the class sessions rather than a finished product. As a result, it asks more questions than answering and contains open trains of thought.

Contents

I. The ‘profit without accumulation’ puzzle

The motivational background for Tristan Auvray and Joel Rabinovich’s analysis is to explain the weakening relationship between profit and domestic investment in industrialised countries since the 1970s. According to Post-Keynesian theory there is a positive relation between profits and investment (Stockhammer, 2005). The theory tells that profit expectations induce investment and that profits, as internal funds allow firms to invest.[1] Further, it is investment that allows the realization of present profits on the demand side and that becomes future productive capacity from which profits will be obtained in future. Investment is thus essential in the competitive struggle with other firms. The evidence, however, shows that among developed countries the aggregate level of real investment has decreased, while at the same time firms secured high profits since the 80s. To explain this puzzle, different explanations have been put forward, both at the macro- and the micro-level (for a summary see Auvray & Rabinovich, 2019). At the micro-level, the ‘profit without accumulation’ puzzle is usually described as a consequence of the shareholder value orientation, i.e. the change in corporate governance to favour free cash flows and financial payouts over real investment or more generally, a reorientation in firm’s preferences from growth to profits (Dallery, 2009; Stockhammer, 2005). This is usually framed as ‘financialisation of non-financial firms’ involving a ‘downsize and distribute strategy’. Empirically studies found support for the ‘shareholder value orientation-thesis’ (Hecht, 2014; Orhangazi, 2008; Tori & Onaran, 2018). Most of them find a negative correlation between financial payouts and real investment for different countries, meaning that parts of the sources for increased distribution of profits comes at the expense of capital accumulation. Figure 1 displays this negative correlation between distribution of profits to shareholders and investment, by depicting gross fixed investment as a ratio of net financial payouts for the whole US economy (in blue), and US listed firms (in red).[2] It indicates that the decrease in investment has been more dramatic for listed companies.

[1] In the classical tradition of Smith, Ricardo and Marx, profitability is the fundamental determinant of the rate of growth of capital stock; but the puzzle holds also from a Kaleckian perspective where

[2] I was not able to replicate the offshoring intensity like it is presented in the paper by Auvray and Rabinovich.

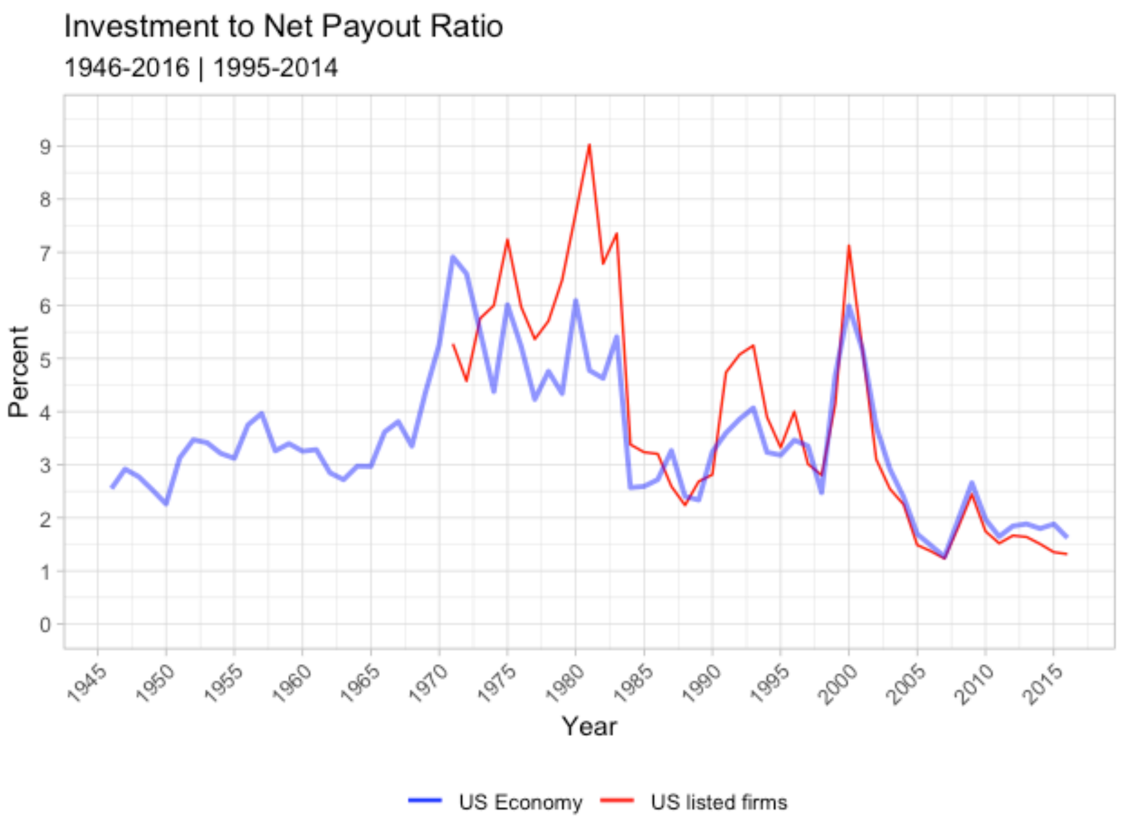

Figure 1. Investment as a ratio of net financial payouts for the US economy and US-listed firms, and offshoring intensity, 1946-2016. *Source:* Compustat and WIOD, Z1 Table, Financial Accounts of the USA, replicated on the basis of Auvray and Rabinovich 2019.

As a consequence to the ‘downsize and distribute strategy’ an increased proportion of funds started to be transferred to shareholders through dividends and, especially for the USA, share buybacks. Figure 2 displays the trend of these financial payouts combined for the US economy (red) and the author’s sample of listed firms (blue) for the period 1971-2016.

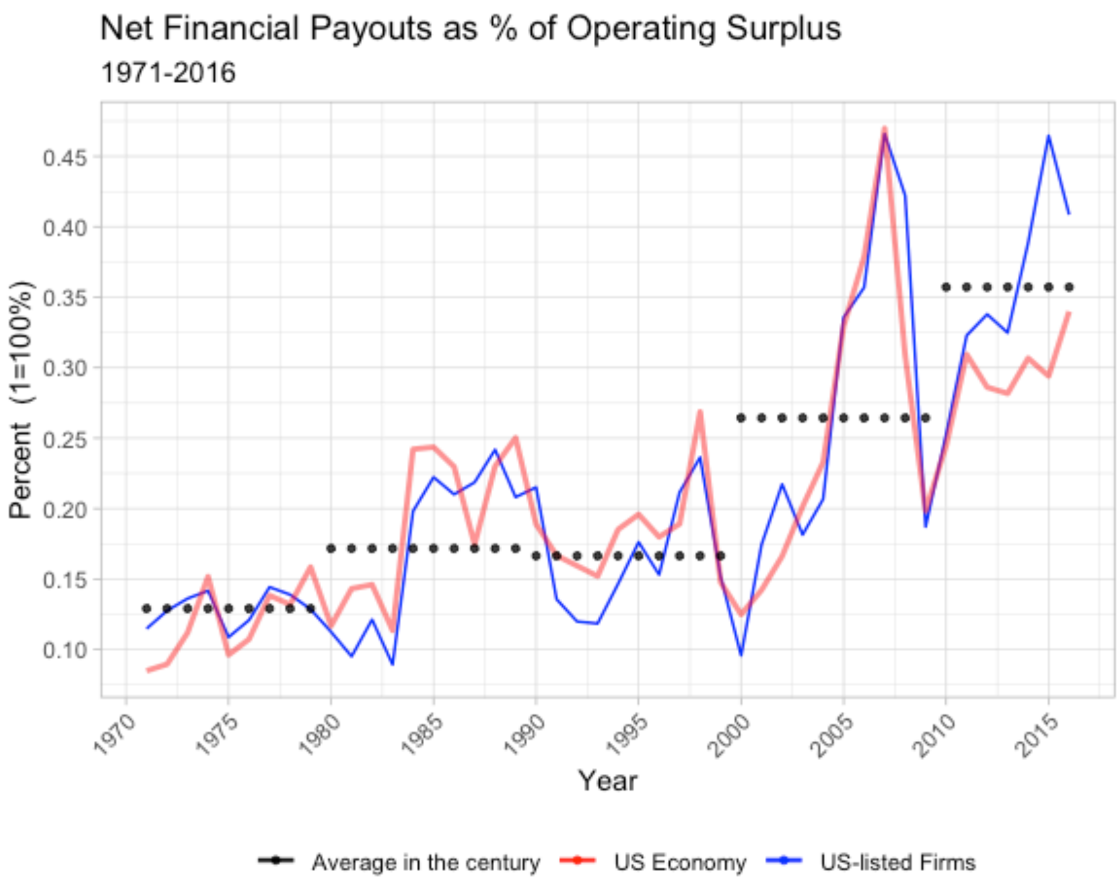

Figure 2. Net financial payouts as percentage of operating surplus for the US economy and US-listed firms, 1971–2016. *Source:* Compustat and WIOD, Z1 Table, Financial Accounts of the USA, replicated on the basis of Auvray and Rabinovich 2019.

Against this background Auvray and Rabinovich are interested in the question as to how firms have been able *to remain* profitable over years, despite the fact that their capacity to supply goods, and, with that one of their main vantage in the competitive struggle has diminished (2019, p. 3). In other words, what accounts for the *sustainability* of low investment and high payouts, while as described above it is generally presumed that today's firm capital accumulation is a prerequisite for its future profitability? Where is the origin of the profits if not in domestic capital formation? To find an answer to this question the authors turn to the globalization literature and establish a link between the internationalization of production or offshoring and financialization and their effects on capital accumulation. The idea is that financialization, i.e. high financial payouts and low capital expenditures, can be sustained over time because profits acquired via managing GVC's cost efficient, render real investment no longer necessary as a source for profitability. In other words the possibility to offshore production is assumed to be one condition, which makes the 'downsize and distribute strategy' sustainable over time and thus an important determinant of capital accumulation. The authors build their proposition on previous work done by Milberg (2008) and Milberg and Winkler (2013; 2010), who indicate that most of the gains associated with offshoring are used to sustain financialisation rather that to invest in productive assets. The more a firm divests from production via offshoring, the more likely it will be financialised:

> “since firms own less productive facilities due to offshoring, profits are not reinvested in inputs, plants and equipment, but redirected to the purchase of financial assets and dividend payments which raises shareholder value” (Auvray & Rabinovich, 2019, p. 10).

Based on this literature and to calculate their investment function, Auvray and Rabinovich build a framework in which they assume that offshoring is in general profitable to the firm but the use of profits – and thus the effect on investment – depends on the organisational setup of offshoring (Auvray & Rabinovich, 2019, p. 11). Their main proposition is that non-core offshoring, i.e. the transfer of non-core/non-strategic production activities to foreign providers, may explain the prevalence of firms with low investment and high financial payouts. To this purpose the authors graphically display the trend in both non-core offshoring and payout-to-investment ratios for firms belonging to different industries. The scatterplots in Figure 5 present the payout-to-investment ratio on the horizontal axis and the offshoring in the vertical axis for the 31 sectors included in the study.

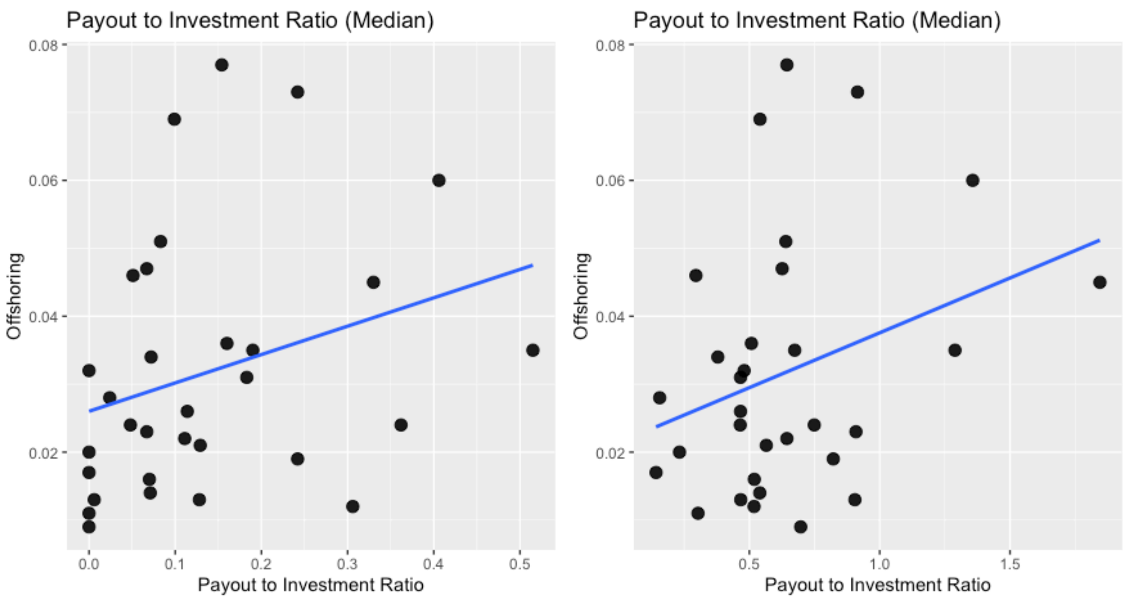

Figure 5.[3] Payout to Investment Ratio, i.e. dividends and share repurchases over capital expenditures. *Source:* Compustat and WIOD, replicated on the basis of Auvray and Rabinovich 2019.

The authors add these scatterplots at an early stage of their analysis to explore the data and to show that offshoring and financialisation is not homogenous across sectors and firms and thus requires targeted analysis. The plots show generally that the more 'off-shored' the firm (i.e. belonging to a more offshored sector), the higher its payout-to-investment ratio. The firms in the 75th percentile are the more financialised companies, with the relationship between offshoring and payouts becoming stronger. However, the fitted line and reveals that the positive linear relationship or correlation between the two variables is not very strong. Furthermore, scatterplots only show the relationship or an association between two variables, so although the payout-to-investment-ratio, plotted on the x-axis, might be considered as an explanatory variable, there is not necessarily a cause and effect relationship. Both variables could be related to some third variable that explains their variation or there could be some other cause. And in fact the causal relationship the authors seem to assume in their exercise goes from offshoring to financialisation and not the other way around, however this is never really specified.

II. The regression specification

To assess to what extend financialisation and offshoring are related phenomena in the accumulation slowdown, the authors specify an investment function that acknowledges the importance of internal funds for investment decisions. They baseline model is defined as follows:

$$\frac{I}{K} = f\left\{\frac{I_{t-1}}{K}, \frac{\pi}{K}, \frac{S}{K}, Q, \frac{LONGDEBT}{K}, \frac{INTEXP}{K}, \frac{INTINC}{K}, \frac{DIV}{K}, \frac{STKISSUE}{K}, \frac{STKREP}{K}, \frac{NETDEBTISSUE}{K}, \frac{INTERNF}{K}\right\}$$

I = capital expenditure (> 0)

K = net property

π = operating income (> 0)

S = sales (> 0)

Q = Tobin's q, the ratio of firms' market capitalisation and book liabilities over total assets (> 0)

LONGDEBT = long debt (> 0 / < 0)

INTEXP = interest expense (< 0)

[3] The right scatterplot displaces the payout-to-investment-ratio for the 75th percentile. The spelling mistake was noticed during the last review of this report and thus not corrected for. The authors displace the median and the 75th percentile because the mean is distorted by extreme values in some industries.

INTINC = interest and investment income (> 0 / < 0)

DIV = common and preferred stock dividends paid (< 0)

STKISSUE (> 0) and STKREP (< 0) = issuance and repurchase of common and preferred stock

NETDEBTISSUE = difference between the sale and purchase of short- and long-term debt (> 0)

INTERNF = firm's balance sheet value of cash and short-term securities (proxy for internal cash flow) (> 0)

All these variables are captured by Compustat data. The authors follow the Post-Keynesian convention and take the lags of the explanatory variables. Moreover, they divide the variables by the capital stock to correct for heteroscedasticity and for firm size. The statistical specification is the following, where γ_{it} is the coefficient of the age of the corporation, β_t are coefficients of a set of time dummies and ε_{it} represents non-observable shocks:

$$\ln\left(\frac{I}{K}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{I}{K}\right)_{i,t-1} + \alpha_2 \ln\left(\frac{\pi}{K}\right)_{i,t-1} + \alpha_3 \ln\left(\frac{S}{K}\right)_{i,t-1} + \alpha_4 \ln(Q)_{i,t-1} + \alpha_5 \ln\left(\frac{LONGDEBT}{K}\right)_{i,t-1} + \alpha_6 \ln\left(\frac{INTEXP}{K}\right)_{i,t-1} + \alpha_7 \ln\left(\frac{INTING}{K}\right)_{i,t-1} + \alpha_8 \ln\left(\frac{DIV}{K}\right)_{i,t-1} + \alpha_9 \ln\left(\frac{STKISSUE}{K}\right)_{i,t-1} + \alpha_{10} \ln\left(\frac{SSTKREP}{K}\right)_{i,t-1} + \alpha_{11} \ln\left(\frac{NETDEBTISSUE}{K}\right)_{i,t-1} + \alpha_{12} \ln\left(\frac{INTERNF}{K}\right)_{i,t-1} + \alpha_{13} \ln(COREOFF)_{j,t-1} + \alpha_{14} \ln(NONCORENONENERGYOFF)_{j,t-1} + \gamma_{it} + \sum_{t=1996}^{t=2011} \beta_t + \varepsilon_{it}$$

The authors use a logarithmic function to account for potential non-linearities between explained and explanatory variables. The coefficients α_{13} and α_{14} account for the incorporation of offshoring in the investment function, based on industry-level information from WIOD. Coefficient α_{13} concerns the narrow or core activities of the enterprise, which are measured as *inputs from the same sector*, $COREOFF_j = \frac{II_j^F}{Y_j}$ (> 0)[4]. The coefficient α_{14} concerns the non-core and non-energy activities measured as *inputs from other sectors* excluding energy, $NONCORENONENERGYOFF_j = \frac{\sum_{k \neq j} II_j^F}{Y_j}$ (< 0).

With this specification the authors want to test their hypothesis that a sustained 'downsize and distribute strategy' (low investment and high financial payouts) has been possible for corporations belonging to industries highly involved in global value chains (GVCs). In this line they expect financial payouts to be

> "significantly negatively correlated with investment in capital expenditures for the subsample of firms belonging to industry consuming the highest level of foreign non-core intermediary inputs" (Auvray & Rabinovich, 2019, p. 19).

[4] To limit the effects of domestic outsourcing as much as possible, the authors take the total output Y of each sector as the denominator.

III. Presentation of the databases and methodology

Alain Desrosières introduces the "metadata paradox" (2001, p. 346). It describes the fact that from a *normative standpoint*, users of data should be given a maximum of detailed information on the *data-production process*, and that they themselves have a responsibility to study the sources of data. However, from a *descriptive standpoint* an abundance of metadata means distraction, inefficiency and more work for the *users of data* – normally a "researcher or social player in the administrative, political or economic sphere" (ibid.). Desrosières states that for users of data ideally "'reality' is nothing more than the database to which they have access. Normally, such users do not want to (or cannot) know what happened before the data entered the base. They want to be able to trust the "source" (here the database) as blindly as possible to make their arguments – backed by that source – as convincing as possible" (ibid.). For Desrosières it is important however, especially when applying econometric methods, to acknowledge that data is almost never just "given". Such a perspective neglects the prior stages in the use process of data, i.e. the recording or measuring and coding of the data that always happens from a certain "perspective", i.e. follows certain conventions and therein describes "an investment in form": "Coding always involves sacrificing something with a view to the subsequent use of a standardized variable, that is, *an investment in form"* (ibid., p. 347).

Thus, following a conventionalist approach it is important to study the sources of our data, if we did not produce it ourselves. What kind of institutions built the databases, for what purpose?

The data

To estimate investment functions Auvray and Rabinovich deal with two different databases: world-consolidated firm-level data for US-listed companies from Compustat merged with industry-level information on offshoring from the World Input–Output Database (WIOD). In all cases the authors are dealing with active and inactive, publicly listed non-financial US corporations.

Compustat contains world-consolidated firm-level data for US-listed companies. This presents consolidated data for the parent company along with its national and international subsidiaries. This provides an approximate notion of the worldwide activity of those firms. The fact that the data is consolidated represents an advantage since it includes information from financial subsidiaries. Additionally, Compustat allows us to present an analysis of NFC's total sources and uses of cash based on their Cash Flow Statement. Compustat is produced by Standard and Poor's, S&P Global Market Intelligence, a provider of multi-asset class and real-time data, research, news and analytics to institutional investors, investment and commercial banks, investment advisors and wealth managers, corporations, and universities. The database covers 99,000 global securities, covering 99% of the world's total market capitalization with annual company data history available back to 1950 and quarterly data available back to 1962 (depending when that company was added to the database). In addition to Compustat the authors use the **World Input-Output Database (WIOD)** for the US for information on offshoring. The WIOD stems from a project funded by the European Commission, Research Directorate General from 2009-2012. The project was carried out by a consortium of 12 research institutes headed by the University of Groningen. It is a public database on internationalization of production process and provides time-series of world input-output tables for 40 countries, and a model for the rest of the world. Information is provided, for example, on changes in productivity, changes in income inequality and key figures on developments on the labour markets (Timmer et al., 2013). The tables have been constructed in a conceptual framework on the basis of officially published input-output tables in conjunction with national accounts and international trade statistics. The WIOD 2013 Release, which the authors use, consists of a series of databases and covers 27 EU countries and 13 other major countries in the world for the period from 1995 to 2011. Therein data for 35 sectors is classified according to the International Standard Industrial Classification revision 3 (ISIC Rev. 3 is not available in Compustat, so the authors use the SIC codes of each firm) (Timmer et al., 2015).

I still don't quite understand the use of different level data and the problems that may emerge with that:

_It is not really mentioned whether the firm-level data is compatible with the industry-level data used to measure offshoring and how they are merged – how does that work?

_The matching between two databases is one of the *critical* problems in empirical research and in my opinion is not sufficiently described

_Moreover the authors could make it more transparent when and why they argue at the firm- or sector-level. The core argument is made at the firm-level, the econometric exercises however switch between different levels.

_statements like "portrays trends in both offshoring and payout-to-investment ratios for firms belonging to different industries" are confusing when what the authors actually study in this case are industries not firms.

Estimation methodology

The authors use panel regressions for US non-financial corporations between 1995 and 2011 to measure the combined effect of financialisation and offshoring on aggregate investment or capital accumulation.

Panel data consists of a time series for each cross-sectional unit in the sample. The data contains measurements for (the same!) individual units over a period of time. It combines the dimensions of space and time, i.e. it contains both cross-sectional and time-series characteristics. The advantage of using panel data is that by utilizing repeated information on the individual entities being investigated, we can control for the effects of some missing or unobserved variables. The 'things' we don't observe can be important factors determining our outcome of interest, so dealing with this form of omitted variable bias can be a huge benefit of panel data. We know that the type of data we are using may influence how we estimate our econometric model. For panel data we should not use a standard linear model, we need specialized techniques.

However, there are also some problems that might emerge in dealing with panel data. Making estimations based on panel data may lead to results containing heterogeneity bias. This bias occurs if characteristics are ignored that are unique to the cross-sectional units (relegate those things to the error term) and they're correlated with any of the independent variables. If no measures are taken to control for individual fixed effects, the risk of obtaining biased estimates emerges. The method most commonly used to deal with this issue is the fixed effects estimator. Furthermore, autocorrelation may exist in a regression model when the order of the observations in the data is relevant or important. Thus, with time-series and sometimes panel data, autocorrelation is a concern. When a regression model is estimated using data of this nature, the value of the error in one period may be related to the value of the error in another period, which results in a violation of a classical linear regression model assumption. In the case of the study at hand autocorrelation is expected due to the lagged dependent variable among regressors (Auvray & Rabinovich, 2019, p. 22). There are different ways to test for autocorrelation, Auvray and Rabinovich, for example, use the Arellano-Bond test to test their instruments.

In order to deal with the individual effects and the correlation between the lagged variable and the error term the authors use a generalised method of moment (GMM) procedure proposed by Arellano and Bond (1991). This method uses additional instruments (sometimes quite a lot) based on the orthogonality condition that exists between lagged values of the dependent variable and the error term and also other possible strictly exogenous regressors. On this basis the authors use the 'Arellano–Bond two-step difference GMM estimator' (Auvray & Rabinovich, 2019, p. 23).

IV. Replication of the data cleaning process and the financialisation model

First of all, I was only able to replicate the baseline financialization model for all, small and large firms. However, I was only able to do so with the help of a fellow student who shared his code so that we were able to program it in R by ourselves try and understand the different steps he underwent.

In a first step we tried to reconstruct the different steps to replicate the process of Auvray and Rabinovich in cleaning their data. To arrive at the reduced dataset, we first had to exclude firms without information for the variables essential to our regression. The variables used from the datasets correspond to the regression variables defined by the authors in the following way (Auvray & Rabinovich, 2019, p. 16):

I = (- IQ_CAPEX) (capital expenditure)
K = IQ_NPPE (net plant, property and equipment)
π = IQ_OPER_INC (operating income/profits)
S = IQ_REV (revenues)
Tobins Q = (IQ_MARKETCAP_average+IQ_TOTAL_LIAB)/IQ_TOTAL_ASSETS
(ratio of firms' market capitalisation and book liabilities over total assets)
LONGDEBT = IQ_LT_DEBT (long debt)
INTEXP = (- IQ_INTEREST_EXP) (interest expense)

INTINC = IQ_INTEREST_INCOME + IQ_INC_EQUITY (interest and investment income)
DIV = (- IQ_TOTAL_DIV_PAID_CF) (common and preferred stock dividends paid)
STKISSUE = IQ_COMMON_ISSUED + IQ_PREF_ISSUED (issuance of common and preferred stock)
STKREP = -(IQ_COMMON_REP + IQ_PREF_REP) (repurchase of common and preferred stock)
NETDEBTISSUE = IQ_TOTAL_DEBT_ISSUED - (-IQ_TOTAL_DEBT_REPAID) (difference between the sale and purchase of short-term and long-term debt)
INTFIN = IQ_CASH_ST_INVEST (cash and short-term investment)

So, following the authors, as a first step in cleaning the data we want to remove firms with no information for all years of capital expenditure, sales, net property plant and equipment, long-term debt, interest expenses, cash and short-term securities, total assets, total liabilities and equities. For this purpose we used binary values. We defined that if 1, the firm has no values for any of the years, and if 0, it has at least one value. On this basis we were able to delete companies with incomplete data. As a next step we removed all observations with no information on market capitalisation at the end of the year, with duplicate observations, negative values for interest income and positive values for interest expenses and dividends. We then had to define the variables required for the regression and to this purpose created new variable columns. This involved different steps: To account for outliers, we followed the authors and winsorized observations at the upper and lower 0.5%, i.e. values of each variable were set either at the 0.5th or 99.5th percentile value when they are, respectively, lower or higher than these thresholds. According to the authors their log transformation – used to account for potential non-linearities between explained and explanatory variables – "avoids censorship of firms with variables equal or inferior to zero (those with negative earnings or without stock issues or financial payouts for example): for any variable var, we compute ln(var)= -ln(var + 1) if var < 0, and ln(var) = ln(var + 1) if var>0 (Auvray & Rabinovich, 2019, p. 18)". To do this in R we used the ifelse() function for any variables that return negative values as in the case of π/K: The ifelse function will basically say: "if var > 0, then ln(var +1), otherwise -ln(1-var)". If R produced calculating errors because it tried to take the log of a negative number we replaced them with simple missing values using the “is.nan” function. Finally, we lagged each variable, except of long debt because it is a stock and does not depend on period t-1.

The next big step to understand was splitting the dataset into small and large firms samples. We decided to do so by taking the median of total assets *per year* and around this splitting the database into the largest and smallest firms each year. Through this process we created three different datasets: *Orig.Data* (all companies) *Orig.Data.small* (only the small companies) and *Orig.Data.large* (for all large companies). On these we could run the regressions using the two-step difference GMM estimator, with the following result for all firms:

```
Twoways effects Two steps model

Call:
pgmm(formula = ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
    dplyr::lag(ln_SalesK_0) + dplyr::lag(ln_Q_0) + ln_LongDebtK +
    dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) + dplyr::lag(ln_DivK_0) +
    dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) + dplyr::lag(ln_NetDebtIssueK_0) +
    dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data = Orig.Data,
    effect = "twoways", model = "twosteps", transformation = "d",
    index = c("Company_Name", "year"))

Unbalanced Panel: n = 5243, T = 1-17, N = 38841

Number of Observations Used: 28949

Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-1.2248911  0.0000000  0.0000000 -0.0002897  0.0000000  1.0821864

Coefficients:
                                 Estimate  Std. Error z-value  Pr(>|z|)
dplyr::lag(ln_IK_0)            0.24402223  0.02262916 10.7835 < 2.2e-16 ***
dplyr::lag(ln_ProfitsK_0)      0.01976364  0.00459197  4.3040 1.678e-05 ***
dplyr::lag(ln_SalesK_0)        0.02904838  0.00882880  3.2902  0.001001 **
dplyr::lag(ln_Q_0)            -0.00064063  0.00800833 -0.0800  0.936241
ln_LongDebtK                   0.01009396  0.00434828  2.3214  0.020267 *
dplyr::lag(ln_IntExpK_0)      -0.00389377  0.01955947 -0.1991  0.842205
dplyr::lag(ln_IntIncK_0)       0.00925389  0.04819485  0.1920  0.847734
dplyr::lag(ln_DivK_0)         -0.05242213  0.03719169 -1.4095  0.158684
dplyr::lag(ln_StkIssueK_0)     0.00693411  0.00428506  1.6182  0.105618
dplyr::lag(ln_StkRepK_0)       0.00437148  0.00621297  0.7036  0.481678
dplyr::lag(ln_NetDebtIssueK_0) -0.00569786  0.00225625 -2.5254  0.011558 *
dplyr::lag(ln_IntFinK_0)       0.03964601  0.00591199  6.7060 2.000e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sargan test: chisq(119) = 169.7875 (p-value = 0.0015584)
Autocorrelation test (1): normal = -17.68692 (p-value = < 2.22e-16)
Autocorrelation test (2): normal = 0.3802771 (p-value = 0.70374)
Wald test for coefficients: chisq(12) = 357.0819 (p-value = < 2.22e-16)
Wald test for time dummies: chisq(15) = 714.0372 (p-value = < 2.22e-16)
```

results for small firms_financialization model:

```
Twoways effects Two steps model

Call:
pgmm(formula = ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
    dplyr::lag(ln_SalesK_0) + dplyr::lag(ln_Q_0) + ln_LongDebtK +
    dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) + dplyr::lag(ln_DivK_0) +
    dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) + dplyr::lag(ln_NetDebtIssueK_0) +
    dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data = Orig.Data.small,
    effect = "twoways", model = "twosteps", transformation = "d",
    index = c("Company_Name", "year"))

Unbalanced Panel: n = 3658, T = 1-17, N = 19424

Number of Observations Used: 12467

Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-1.1963521  0.0000000  0.0000000 -0.0001519  0.0000000  1.1737373

Coefficients:
                                 Estimate Std. Error z-value  Pr(>|z|)
dplyr::lag(ln_IK_0)             0.2138666  0.0316836  6.7501 1.478e-11 ***
dplyr::lag(ln_ProfitsK_0)       0.0190287  0.0053806  3.5365 0.0004054 ***
dplyr::lag(ln_SalesK_0)         0.0527408  0.0113618  4.6419 3.452e-06 ***
dplyr::lag(ln_Q_0)              0.0012844  0.0112621  0.1140 0.9092008
ln_LongDebtK                    0.0131100  0.0055081  2.3801 0.0173063 *
dplyr::lag(ln_IntExpK_0)       -0.0093097  0.0199647 -0.4663 0.6409949
dplyr::lag(ln_IntIncK_0)        0.0136623  0.0638446  0.2140 0.8305524
dplyr::lag(ln_DivK_0)          -0.0230688  0.0568611 -0.4057 0.6849600
dplyr::lag(ln_StkIssueK_0)     -0.0017803  0.0052600 -0.3385 0.7350121
dplyr::lag(ln_StkRepK_0)        0.0106498  0.0119255  0.8930 0.3718390
dplyr::lag(ln_NetDebtIssueK_0) -0.0056671  0.0031992 -1.7714 0.0764936 .
dplyr::lag(ln_IntFinK_0)        0.0457920  0.0088382  5.1811 2.205e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sargan test: chisq(119) = 116.3452 (p-value = 0.55174)
Autocorrelation test (1): normal = -12.79639 (p-value = < 2.22e-16)
Autocorrelation test (2): normal = 1.071244 (p-value = 0.28406)
Wald test for coefficients: chisq(12) = 205.2938 (p-value = < 2.22e-16)
Wald test for time dummies: chisq(15) = 249.4921 (p-value = < 2.22e-16)
```

Results for large firms_financialization model:

```
Twoways effects Two steps model

Call:
pgmm(formula = ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
    dplyr::lag(ln_SalesK_0) + dplyr::lag(ln_Q_0) + ln_LongDebtK +
    dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) + dplyr::lag(ln_DivK_0) +
    dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) + dplyr::lag(ln_NetDebtIssueK_0) +
    dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data = Orig.Data.large,
    effect = "twoways", model = "twosteps", transformation = "d",
    index = c("Company_Name", "year"))

Unbalanced Panel: n = 2485, T = 1-17, N = 19417

Number of Observations Used: 15466

Residuals:
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-0.9386138  0.0000000  0.0000000 -0.0006959  0.0000000  0.9343762

Coefficients:
                               Estimate  Std. Error z-value  Pr(>|z|)
dplyr::lag(ln_IK_0)            0.26639107  0.03549303  7.5054 6.122e-14 ***
dplyr::lag(ln_ProfitsK_0)      0.02965194  0.00720815  4.1137 3.894e-05 ***
dplyr::lag(ln_SalesK_0)       -0.01759814  0.01039075 -1.6936  0.090334 .
dplyr::lag(ln_Q_0)             0.01382259  0.00848780  1.6285  0.103414
ln_LongDebtK                   0.01077497  0.00814144  1.3235  0.185678
dplyr::lag(ln_IntExpK_0)      -0.06097019  0.03293697 -1.8511  0.064153 .
dplyr::lag(ln_IntIncK_0)       0.02832461  0.05263152  0.5382  0.590461
dplyr::lag(ln_DivK_0)         -0.04142983  0.03708987 -1.1170  0.263989
dplyr::lag(ln_StkIssueK_0)     0.01842828  0.00658678  2.7978  0.005146 **
dplyr::lag(ln_StkRepK_0)      -0.00840431  0.00593628 -1.4158  0.156847
dplyr::lag(ln_NetDebtIssueK_0) 0.00078778  0.00271064  0.2906  0.771337
dplyr::lag(ln_IntFinK_0)       0.03069757  0.00602665  5.0936 3.513e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sargan test: chisq(119) = 180.5541 (p-value = 0.00023494)
Autocorrelation test (1): normal = -9.74665 (p-value = < 2.22e-16)
Autocorrelation test (2): normal = -2.35439 (p-value = 0.018553)
Wald test for coefficients: chisq(12) = 202.1107 (p-value = < 2.22e-16)
Wald test for time dummies: chisq(15) = 593.4703 (p-value = < 2.22e-16)
```

The results we obtained are not the same as the ones Auvray and Rabinovich find. First of all our observations vary in number, although not to a major degree. Regarding the financial payouts channel, dividends have a negative elasticity of 0.05 but are not significant anymore. Stock repurchases become positive with 0.004, and non-significant. This does not really change for large firms, except that stock repurchases now turn negative, still non-significant. None of the elasticity of financial payout variables becomes significant as it is in the case of the author's analysis. Regarding the financial income channel, we find positive but non-significant effects in all three samples. Although our elasticities are not the same this is in line with the results from Auvray and Rabinovich. Above that we find a positive and statistically significant effect of INTFINK at the 1 per cent level, meaning internal funds are important for investment contrary to the squeeze of retained earnings argument found in the literature. This is in line with the result of the authors. Concerning our results for the control variables net debt issue becomes negative and significant for all and positive but non-significant for large firms. This diverts from the result of Auvray and Rabinovich, who obtain positive and significant results for all samples. Stock issue is only positive and significant for the large firms. We had problems with defining the variable Tobin's q, why the results are complete humbug. At least sales, profits and past investment are all positive and significant for all samples. LongDebtK is positive but non-significant for large firms and significant for the all and small sample, here the authors find negative and non-significant results for all samples. IntExpK is significant only for large firms with a negative elasticity of 0.06.

In summary, the results we obtained are quite disappointing because we were only able to replicate the baseline financialisation model and even here we did not really find support for the basic claim found in the literature that financialisation in the form of financial payouts has a negative impact on investment.

V. Critical assessment

This part contains three elements. First, I will critically examine the variables used by Auvray and Rabinovich, then I will comment on their offshore measure and finally try to assess the value of their exercise in the academic inquiry of understanding the specificities and workings of modern capitalism.

Quantification and Measurement

> "If you think you know something about a subject, try to put a number on it. If you can, then maybe you know something about the subject. If you cannot then perhaps you should admit to yourself that your knowledge is of a meager and unsatisfactory kind."
>
> ~ Lord Kelvin, 1893

If one wants to take a critical approach to the construction and use of statistics it is helpful to follow Alain Desrosières (2001; 2008b, 2008a; 2014). Desrosières is internationally known for his works on quantification and its relation to political economies. More recently Desrosières' strand of research on quantification has been continued especially by Salais (2012), Thévenot (2011) and Diaz-Bone (2016; 2016). His work stands in the tradition of the pragmatist and socio-economic institutional approach labelled 'convention theory' or the economics of conventions, which is part of the so-called new pragmatist French social sciences and a main contribution of new economic sociology. The core assumption of this research is that economic value and worth have to be interpreted and constructed according to situations of economic coordination. Economic actors therefore rely on conventions as socio-cultural frames for mobilizing a shared interpretation of the objects, actions, goals, and collective intentions involved in situations of production, distribution, and consumption.

Concerning quantification Desrosières distinguishes between four approaches to reality, each having a different *reality test* – "that is, ways of verifying and articulating the substance of that reality and its independence from observation" (2001, p. 340). A conventionalist researcher approaches "reality" by emphasising the *conventional and social character of statistical variables* and in this differs from the more 'realistic' approaches. Statistical tools are seen to always develop in context, in order to answer a specific scientific question. Thus data and reality are fundamentally different things. Further, in this view computed moments do not simply reflect an underlying macrosocial reality, revealed by those computations. The presumably "external reality" of the objects is challenged. Objects do not exist independently of any judgment or measuring procedure and evidences of original coding act and remain visible and important throughout the process. In this light it is important to understand that the specific way that variables are constructed and how they are interpreted is not fixed or 'real' in any sense. I want to focus on two variables used by Auvray and Rabinovich: net financial payouts and capital expenditures.

The difference between quantification and measurement

Quantification is a certain way of thinking about/looking at something and finding an objective language to talk about it (e.g. climate change=CO2 emissions). In doing so, the properties of an object or fact are reformulated into measurable quantities and numerical values. The prerequisite for this is the definition of a quantifiable variable and the specification of a quantification method. Comparability arises from the application of the same procedure to different things or situations. **Measurement** means to ascertain the quantity of a unit of material via calculated comparison with respect to a standard. It is about seeing more objectively what's happening in "the world".

Net Financial Payouts Variable

For figure 1 and figure 2 the authors calculate net financial payouts for US firms as follows: stock repurchases + dividends paid – stock issue. This variable excludes dividends received from affiliates and interest expenses. Interest expenses are however included by Orhangazi (2008) amongst others. As it is a net variable the measure then also excludes income from interest and financial investment. It seems like the authors are solely focussing on payouts, probably so because they want to distinguish the two channels of financialisation of non-financial firms. It is important to distinguish between the different ways in which the financial payout measure is constructed in the literature. Durand and Gueuder (2018) for example include financial income and find diminishing or at least stable net payouts for most of the analysed countries. Moreover, it is important to acknowledge that the financial payout measure can mask important qualitative changes. Now we are in a phase marked by low interest rates, and the time period studied by the authors excludes the time around the 1990s, when the weight of interest payments relative to profits of non-financial corporations peaked. Instead their variable is rather marked by rising claims of shareholders, however, this relation is subject to change.

Capital Expenditure Variable

Another interesting variable to look at is capital expenditures, which is reflected by the variable ‘CAPX’ in Compustat. Compustat defines, CAPX as representing “the funds used for additions to property, plant, and equipment, excluding amounts arising from acquisitions (for example, fixed assets of purchased companies). This item includes property and equipment expenditures” (Cumpustat User’s Guide 2003, p. 212). This measure does not include intangible assets. The authors do not discuss what the implications of the exclusion of intangibles are for their results. The question for example in how far intangible investment has substituted physical investment is not assessed. The problem is that for many intangible investments there are still no valuation standards, as there is generally no market and no market prices for them. One particular difficulty with these assets is the way in which they have been traditionally treated under accounting rules:

> “Internally generated intangibles—through R&D (patents and trademarks), marketing (brands, customer relations), development (business processes), or training (human resources)—are treated like regular expenses (charged immediately to income), whereas the same intangibles, if acquired, either directly, like patents or brands, or through corporate acquisitions (R&D-in-process, customers lists), are considered assets and capitalized and, then, some are amortized” (Lev & Gu, 2016, p. 83).

More recently, the role played by intangible investment and its relation both with financialisation and offshoring has been put in the spotlight by Durand and Milberg (2018) and Orhangazi (2019). While offshoring allows firms to increase production and decrease costs per unit of investment, intangible investment is usually associated to monopoly rents increasing therefore prices. The paper by Orhangazi focuses on the increasing importance of economic assets arising from a greater mastery of information and data as one possible explanation for the ‘profit without accumulation’ puzzle. For him intangible assets are important as they enable firms to increase market power and profitability without having to increase investment in fixed capital correspondingly (ibid., 27). Gutiérrez and Phillipon (2017) also find that industries with higher share of intangibles exhibit lower physical investment.

→ Question: do total assets include intangibles? Because if not then this would be a problem for the authors’ method of controlling for the size of the firms…

The offshoring measure

The hypothesis of Auvray and Rabinovich is that the ‘downsize and distribute’ strategy (low investment and high financial payouts) has been possible for firms belonging to industries highly involved in GVCs. The authors argue that comprehensive information on offshoring is not available for individual firms. Hence, rather than studying the offshoring of corporations, they consider the offshoring of their respective industry. This leads them to study how offshoring on an industry level affects capital expenditures on a firm level. In other words the focus is on capital accumulation behaviour of firms, conditional on the fact that firms belong to industries with various degrees of offshoring. Does this empirical strategy make sense? What are possible problems that emerge with it?

It seems to me as if the authors ignored the large literature on trade theory and its major developments within in the last years. The references they use concerning international trade and offshoring are from the 90s, however, since then trade theory changed in major ways. Most importantly firm-level theories and empirical investigations replaced country and industry level analysis. This recent literature shows that the international trade landscape is characterized by a significant rise of *intra-industry trade* (which would be core-offshoring in the authors framework) and *huge multinational firms* organizing global production networks along global supply chains (Melitz & Trefler, 2012; Yi, 2003). Various studies show that “only the most productive firms can benefit from enhanced opportunities for foreign sourcing and production” (Kim & Osgood, 2018). According to Bernard et al. (2009) US-based multinationals are mediating more than 90% of US trade. It seems to me that these insights have not really been considered by the authors who build their whole theoretical framework around the fact that offshoring is profitable for all firms (Auvray & Rabinovich, 2019, p. 11). However, the fact that the essential factor determining the results the authors seek is likely to be the size of firms is not stressed sufficiently in my opinion. Is it not a problem that the authors assume that all firms in a sector offshore to the same degree, i.e. to the degree their industry offshores? New new trade theory explicitly stresses the heterogeneity of firms belonging to an industry with regard to offshoring (Melitz & Trefler, 2012). The differences in offshoring are not so much across industries but across firms.

Moreover, I see a problem with how they measure non-core and core offshoring. Originally the distinction between core and non-core activities is based on the competencies of a firm, rather than its products (Prahalad and Hamel, 1990). However, because the authors use industry-level data they define core (non-core) offshoring of a given industry by the import of inputs that belongs to the same (a different) two-digit Standard Industrial Classification industry. On this basis the authors also assume that non-core offshoring is basically inputs by foreign producers not affiliates. The measures the authors use for non-core and core offshoring are not able to distinguish between the production offshored to affiliates and that to other enterprises. This assumption is essential for it determines the expected effect on investment. But then I don't understand why the authors only use the primary SIC codes. This is the main code that categorizes the core industry of the business. Businesses can however also have up to five secondary SIC codes. Secondary SIC codes classify other industries the business is involved in but aren't the main focus. Wouldn't it have made sense to include these secondary codes in their analysis to control for affiliates?

Concerning the rise of intra-industry trade is might be questioned that the authors assume that non-core offshoring is the main source of declining domestic real investment and therefore the background to the 'downsize and distribute' strategy. Just because firms receive inputs from the same sector (i.e. what is considered to be core offshoring by the authors) does not have to mean that these are inputs by affiliates. Intra-industry trade has been rising significantly and thus only focusing on non-core offshoring might neglect important effects of what the authors understand as core offshoring on investment.

In sum, it seems to me as if the way the authors deal with offshoring is a bit out-dated. Feenstra for example argues that early research on offshoring indeed used the cost share of imported intermediate inputs in each industry as a measure of offshoring (Feenstra, 2017). However, in a world with globalized production, the share of inputs that are imported becomes more and more difficult to measure when goods cross border multiple times (ibid.). According to Feenstra as a result "second generation" measures of offshoring developed from global input-output tables.

Situating the results within the academic debate

First of all, the analysis by Auvray and Rabinovich makes clear that we have to conceptually understand the financialisation of non-financial corporations as a twofold phenomenon (Orhangazi, 2008): on the one hand, firms increase their financial payments to shareholder, financial markets and institutions; on the other hand, firms accrue their profits through financial channels rather than through trade and production. The author's analysis questions the empirical validity of the second phenomenon and thereby point to a fundamental argument between different scholars of the Post-Keynesian and Marxist tradition (see Mavroudeas & Papadatos, 2018). The *financial turn of accumulation* hypothesis maintains that capitalism has undergone a radical structural transformation during the last three decades. In this reading the financial system has converted the whole system according to its own prerogatives. A new stage of capitalism - financialised capitalism - has been reached, fundamentally altering the process of accumulation and profit creation. This narrative suggests a substitution of financial investments at the expense of real investments as the strategy of lead firms shifted towards higher short-term profitability through financial incomes at the expense of productive investment. But does this financialization hypothesis comprehend the actual workings of modern capitalism? Auvray and Rabinovich's analysis gives little support to the narrative that the productive sectors of the capitalist economy, has turned into rentiers or financialised agents getting most of their profits from 'extraction' of interest, rent or capital gains (see also Rabinovich, 2019). Rather their work shows that globalisation, which paved the way for the internationalization of production, is important for the profitability of big firms and that financialisation is *not* a uniform process. Thus, the analysis shows that financialisation is *a phenomenon, which should be analysed in relation to the sphere of production and the latters organization via varying business models.* The fundamental logic of capitalism did not change. The enormous expansion of global value chains has brought a lowering of input costs to lead firms, allowing them to maintain and even increase cost mark-ups, and thus profit rates and the economy-wide profit share. Large oligopoly firms have not raised their prices but have managed to expand their profits as they capture, through cheaper imports (mark-up effect), various gains tied to labour exploitation, realised along global value chains in developing economies (William Milberg, 2008). The system of low investment and high profits is stable over time because of the asymmetric organization of the production process through GVCs that describes some sort of externalisation of exploitation from the global North to the global South (Contractor et al., 2010). This supports Classical Marxism that argues that modern financial developments are always related to production and, hence, cannot be understood independently from the latter and that capitalism needs an ‘outside’ to reproduce and stabilize itself through a process of expansion. The relationship between profits and investment might be historically contingent and evolves through space and time, capitalisms flourishing through deeper processes of exploitation and domination, however, follow the same basic logic.

VI. R Code

4.1 Figure 1

Shows the negative correlation between distribution of profits and investment, by showing the ratio between gross fixed investment and net financial payouts for the whole US economy, and US listed firms. The replicated figure fails to display the offshoring activity verified since the mid-90s, which can be found in the original graph.
Variables:

- Net Financial Payouts, US economy = Dividends Paid - Equity and Investment Fund Shares
- Investment, US economy = Gross Fixed Capital Formation
- Net Financial Payouts, US firms= Stock Repurchases + Dividends Paid - Stock Sales
- Investment, US firms = Capital Expenditures

Source: Table Z1, Financial Accounts of the USA and Compustat and WIOD.

R Code Figure 1

```
# Installation of necessary packages
install.packages("tidyverse")
library(tidyverse)
library(scales)

#let R know my path
setwd("~/Desktop/Master courses/Paris/Heterodox Econometrics and quantitative methods")
```

 # Figure1: with compustat

```
# import and clean compustat
compustat<- read.csv("./compustat.csv", header=TRUE,sep=";",dec = ",")
head(compustat)

fig1.compustat<-as_tibble(compustat)
%>% select(-c(X)) %>% filter(year>1945)%>%
rename(purchase.stock=prstkc,sale.stock=sstk,
      dividends=dv,capital.expenditure=capx) %>%
  mutate(net.payout=purchase.stock+dividends-sale.stock,ratio=capital.expenditure/net.payout)
head(fig1.compustat)
# With the upper as_tibble command I put the something in "a pipe" which is basically a way to work on the dataset. This will be a basic step, which will be used throughout this R-Code.
#with the filter () command I select only the years above 1945
#We rename the variables in order to make the script easier to read. With the mutate command I am able to work on some specific variables, i.e. rename or redefine them.

ggplot(fig1.compustat,aes(x=year,y=ratio))+geom_point()+ geom_line(color="red",size=2,alpha=0.3) +
ggtitle("Investment as a ratio of net financial payouts for the US economy and US-listed firms")+
xlab("year") + ylab("Investment as a ratio of net financial payouts")
```

 # Figure1: with Z1 dataset

```
# Z1 data is for 'US economy' depiction
#Import and clean Z1
Z1<- read.csv("./Z1.csv", header=F,sep=";",dec = ",",skip=5)
names(Z1)<-names(read.csv("./Z1.csv", header=T,nrows=0, sep=";"))
head(Z1)
#I don't import the first 5 lines with text
#so that R sees that the data is numeric
#but then I have to import again the column names (header)
#I select a set of variables by their column number and rename them
#The command names() is just used in order to reimport the column names

fig1.Z1<-as.tibble(Z1) %>% select(year=1,operating.surplus=9,
  consumption.of.capital=3,18,equity.liability=67,fixed.capital.formation=29) %>%
  filter(year>1945) %>%
  mutate(net.payouts=dividends.paid-equity.liability,ratio=fixed.capital.formation/net.payouts)
head(fig1.Z1)
#Here I select a set of variables by their column number and rename them. The numbers stand for the particular variables in the Dataset Z1.
#with the filter () command I select only the years above 1945


ggplot(fig1.Z1,aes(x=year,y=ratio,color="US Economy"))+
  geom_line(data=fig1.compustat,aes(x=year,y=ratio,color="US listed firms"))+
  geom_line(size=1,alpha=0.5)+
  labs(title="Investment to Net Payout Ratio", subtitle="1946-2016 | 1995-2014") +
  scale_x_continuous(name="Year", breaks=seq(1945, 2015, 5), limits=c(1946, 2016))+ ##definiert die Achsenbeschriftungen
  scale_y_continuous(name="Percent", breaks=seq(0, 9, 1), limits=c(0, 9.5))+
  theme_light()+
  labs(color="legend")+
  scale_color_manual(values=c("blue", "red"))+
  theme(axis.text.x = element_text(angle=45, hjust = 1), legend.title = element_blank(), legend.position = "bottom", legend.direction = "horizontal")+
  guides(col=guide_legend(ncol=2))

#to get the figure in percentage install library(scales) and write scale_y_continuous(labels= percent)
```

4.2 Figure 2

Figure 2 displays the trend of financial payouts for the US economy and for the sample of listed firms from Compustat. More specifically it shows net financial payouts as a percentage of operating surplus.
Variables:

- Operating Surplus - U.S. Economy = Net Operating Surplus + Consumption of Fixed Capital, Structures, Equipment, and Intellectual Property Products, including Equity REIT Residential Structures
- Operating Surplus - U.S. Listed Firms = Pretax income - Income Taxes + Interest Expense + Depreciation and Amortization

Source: Table Z1, Financial Accounts of the USA and Compustat.

Variables in compustat:
Xint - interest and related expense Total
pi - pretax income
txt - income taxes
dp - depreciation and amortization
ibc - income before extraordinary items (cash flow)
sstk - sale of common and preferred stock
prstkc - purchase of common and preferred stock
dv - cash dividends (cash flow)
capx - capital expenditures

Since operating surplus is defined as above, operatingsurplus = pi-txt+Xint+dp

R Code Figure 2

```
#Figure2: with Z1
from Z1:
Define US.economy=net.payouts/(operating.surplus+consumption.of.capital)
Define US.listed.firms=net.payouts/operating.surplus
Net payouts at firm level: net_payout=purchase.stock+dividends-sale.stock

fig2.Z1<-as_tibble(Z1) %>%
  select(year=1,operating.surplus=9,
       consumption.of.capital=3,dividends.paid=18,equity.liability=67,fixed.capital.formation=29) %>%
  filter(year>1945) %>%
  mutate(net.payouts=dividends.paid-equity.liability,ratio=fixed.capital.formation/net.payouts) %>%
  mutate(US.economy=net.payouts/(operating.surplus+consumption.of.capital))
head(fig2.Z1)
ggplot(fig2.Z1,aes(x=year,y=US.economy))+geom_line(color="red",size=2,alpha=0.3)


# Figure2: with compustat
fig2.compustat<-fig1.compustat %>%
  mutate(net.payouts=purchase.stock+dividends-sale.stock)%>%
  mutate(US.listed.firms=net.payouts/(pi+Xint+dp-txt))%>%
  mutate(decade=floor(year/10)*10) %>%
group_by(decade) %>%
  mutate(average=mean(US.listed.firms)) %>% ungroup(decade)
```

#first I group the data into 10-year groups by dividing the years by 10 (1952/10=195.2), floor(195.2) = 195, 195 * 10 = 1952. R then only looks at 195

#ungroup: everything between group and ungroup is programmes on the basis of the grouping

head(fig2.compustat)

#Plotting figure2

```
ggplot(fig2.Z1,aes(x=year,y=US.economy, colour="US Economy"))+
  geom_line(data=fig2.compustat,aes(x=year,y=US.listed.firms, colour="US-listed Firms"))+
  geom_line(size=1,alpha=0.5)+
  geom_point(data=fig2.compustat,aes(x=year, y=average, colour="Average in the centu-ry"),size=1,alpha=0.8)+
  labs(title="Net Financial Payouts as % of Operating Surplus", subtitle="1971-2016", x="Year", y="Percent  (1=100%)", color = "Legend")  +
  scale_color_manual(values=c("#fe93a9", "#65ce93", "#6b5237", "#4e9bac", "#3C3B6E", "#B22234")) +
  scale_x_continuous(breaks=seq(1950, 2020, 5), limits=c(1971, 2016)) +
  scale_y_continuous(labels=, breaks=seq(0.05, 0.5, 0.05)) +
  theme_light()+
  labs(color="legend")+
  scale_color_manual(values=c("black", "red", "blue"))+
  theme(axis.text.x=element_text(angle=45, hjust=1), legend.title=element_blank(), legend.position = "bottom", legend.direction="horizontal")+
  guides(col = guide_legend(ncol = 3))
```

4.3 Figure 5

Displays the main proposition that non-core offshoring may explain the prevalence of firms with low investment and high financial payouts. Scatter plots present the payout-to-investment ratio in the horizontal axis and offshoring in the vertical axis for the 31 sectors of our study.
Variables: non-core non-energy offshoring=share of foreign input in total output, payout-to-intvestment ratio=dividends and share repurchases over capital expenditures
Source: WIOD and Compustat.

R Code Figure 5

```
install.packages("tidyverse")
library(tidyverse)

setwd("~/Desktop/Master courses/Paris/Heterodox Econometrics and quantitative methods")

fig5<- read.csv("./fig5.csv", header=TRUE,sep=";",dec = ".")
#to decide whether "," or "." to use for separation of decimals chose dec = "," or dec = "."

head(fig5)

#Here I rename the variables
names(fig5)[3] <-"noncorenonenergyoffshoring_mean"
names(fig5)[2] <-"sectors"
names(fig5)[4] <-"Payouttoinvestmentratio_mean"
```

```
names(fig5)[5] <-"Payouttoinvestmentratio_p50"
names(fig5)[6] <-"Payouttoinvestmentratio_p75"

#offshoring and financialisation is not homogenous across firms and/or sectors that’s why authors add scatter plots
#figure5bottomleft
sca5.50 <- ggplot(fig5, aes(x=Payouttoinvestmentratio_p50,y=noncorenonenergyoffshoring_mean))+
  geom_point(color="black",size=6,alpha=0.9)+
  geom_smooth(method="lm", se=FALSE)+
  labs(x="Payout to Investment Ratio", y="Offshoring")+
  ggtitle("Payout to Investment Ratio (Median)")
#geom_smoth: used for making the line (linear regression) in the data
#call for help with ?geom_smoth to receive info

#figure5bottomright – more financialised companies
#the line is steeper for those firms that are more offshored and have a higher payout-to-investment ratio, the higher one the higher the other - so there is a relationship that becomes stronger
sca5.75 <- ggplot(fig5, aes(x=Payouttoinvestmentratio_p75,y=noncorenonenergyoffshoring_mean))+
  geom_point(color="black",size=6,alpha=0.9)+
  geom_smooth(method="lm", se=FALSE)+
  labs(x="Payout to Investment Ratio", y="Offshoring")+
  ggtitle("Payout to Investment Ratio (Median)")

#in order to diplace the two graphs besides each other we make the following steps:
install.packages("gridExtra")
library(gridExtra)
grid.arrange(sca5.50,sca5.75,ncol=2,nrow=1)

#Regression in order to look at the linear model
res1 <-lm(data=fig5, noncorenonenergyoffshoring_mean~Payouttoinvestmentratio_p50)
summary(res1)

#MORE DETAILED
#residuals vs Leverage:
lm50.1<- lm(noncorenonenergyoffshoring_mean ~ Payouttoinvestmentratio_p50, data=fig5)
plot(lm50.1)

#residuals vs fitted: shows residuals
lm50.2<- lm(Payouttoinvestmentratio_p50 ~ noncorenonenergyoffshoring_mean, data=fig5)
plot(lm50.2)

#scale-location: speaks about heteroskedasticity: if line is not flat but steep there is a problem
lm.75.1<- lm(noncorenonenergyoffshoring_mean ~ Payouttoinvestmentratio_p75, data=fig5)
plot(lm.75.1)

#normal Q-Q:
lm.75.2<- lm(Payouttoinvestmentratio_p75 ~ noncorenonenergyoffshoring_mean, data=fig5.2)
plot(lm.75.2)

#sum_up to figure5: plot-graphs are misleading: there is no strong relation
```

4.4 Table 6

```
## From now on I used the code from a friend and try to go through step by step to understand it together with two other friends
## (1) Take database and try to arrive at the reduced database
```

(2) Try to replicate the baseline financialisation model with the reduced database for all firms, large firms and small firms.

```
## Installing tidyverse and plm package
library(tidyverse)
install.packages("plm")
library(plm)

#Uploading the full database
Orig.Data <- read.csv("/database.csv", header=TRUE, na.strings='NA')
Orig.Data <- Orig.Data %>% arrange(Company_Name, year)

## now I start to clean the data as Auvray and Rabinovich do----------------
## First I remove all firms with empty value for the following variables: IQ_CAPEX, IQ_NPPE,
IQ_LT_DEBT, IQ_INTEREST_EXP, IQ_CASH_ST_INVEST, IQ_TOTAL_ASSETS,
IQ_TOTAL_LIAB_EQUITY.
## Also I remove all values with empty market cap, duplicate observations, negative values for interest
income and positive values for interest expenses and dividends.
## Thereto I create a list of company names in alphabetical order.

ComList <- sort(unique(Orig.Data$Company_Name))

##create empty list and fill with binary values: If 1, the firm has no values for any of the years, and if 0, it
has at least one value.
ltdebt = c()
intexp = c()
cashst = c()
for (x in ComList) {
  ltdebt <- c(ltdebt, ifelse(
    is.nan(mean(Orig.Data$IQ_LT_DEBT[Orig.Data$Company_Name == x], na.rm = TRUE))==TRUE,
1, 0
  ))
  intexp <- c(intexp, ifelse(
    is.nan(mean(Orig.Data$IQ_INTEREST_EXP[Orig.Data$Company_Name == x], na.rm =
TRUE))==TRUE, 1, 0
  ))
  cashst <- c(cashst, ifelse(
    is.nan(mean(Orig.Data$IQ_CASH_ST_INVEST[Orig.Data$Company_Name == x], na.rm =
TRUE))==TRUE, 1, 0
  ))
}

## We use "is.nan", because the mean value of only NAs will return a nan. Thus, if all values of a com-
pany are NAs, the mean will equal nan.
## NaNs are calculating errors, which occur when R tries to take the log of a negative number - which is
not possible. NAs are missing values in a dataset.
## Now we create a dataframe, by combining the company names with these lists of binary values from
above:
ComList <- as.data.frame(ComList)
Orig.Data.missingvals <- cbind(ComList, ltdebt, intexp, cashst)
names(Orig.Data.missingvals)[1] <- "Company_Name"

## Now I create a column that indicates whether the firm has any values = 0: missing > 0
Orig.Data.missingvals <- mutate(Orig.Data.missingvals, missing=(ltdebt+ intexp+ cashst))

## Then I drop other columns and only keep the names of the companies that should be deleted:
Orig.Data.missingvals <- Orig.Data.missingvals %>% filter(missing > 0)

## Now I can remove all companies from the main dataframe that are in this list:
remov <- Orig.Data.missingvals$Company_Name
Orig.Data <- Orig.Data[!Orig.Data$Company_Name %in% remov, ]
```

```
## 350 observations are removed. I add missing 0 values to following variables (over 10% NA variables, with very under 10 0s):
IQ_INTEREST_INCOME, IQ_INTEREST_EXP YES, IQ_TOTAL_DIV_PAID_CF YES 23854 - no 0, IQ_COMMON_ISSUED YES, IQ_PREF_ISSUED YES
## IQ_COMMON_REP YES, IQ_PREF_REP YES, IQ_TOTAL_DEBT_ISSUED, IQ_TOTAL_DEBT_REPAID

Orig.Data$IQ_INTEREST_EXP[is.na(Orig.Data$IQ_INTEREST_EXP)] <- 0
Orig.Data$IQ_INTEREST_INCOME[is.na(Orig.Data$IQ_INTEREST_INCOME)] <- 0
Orig.Data$IQ_TOTAL_DIV_PAID_CF[is.na(Orig.Data$IQ_TOTAL_DIV_PAID_CF)] <- 0
Orig.Data$IQ_COMMON_ISSUED[is.na(Orig.Data$IQ_COMMON_ISSUED)] <- 0
Orig.Data$IQ_COMMON_REP[is.na(Orig.Data$IQ_COMMON_REP)] <- 0
Orig.Data$IQ_PREF_ISSUED[is.na(Orig.Data$IQ_PREF_ISSUED)] <- 0
Orig.Data$IQ_PREF_REP[is.na(Orig.Data$IQ_PREF_REP)] <- 0
Orig.Data$IQ_TOTAL_DEBT_ISSUED[is.na(Orig.Data$IQ_TOTAL_DEBT_ISSUED)] <- 0
Orig.Data$IQ_TOTAL_DEBT_REPAID[is.na(Orig.Data$IQ_TOTAL_DEBT_REPAID)] <- 0

## Other removals following the approach of the authors in their paper
## remove all observations with empty market cap, duplicate observations, negative values for interest income and positive values for interest expenses and dividends
Orig.Data <- Orig.Data %>%
  filter(is.na(Orig.Data$IQ_MARKETCAP_end_of_year) == FALSE)

Orig.Data <- Orig.Data %>%
  filter(Orig.Data$IQ_INTEREST_INCOME >= 0) %>%
  filter(Orig.Data$IQ_INTEREST_EXP <= 0) %>%
  filter(Orig.Data$IQ_TOTAL_DIV_PAID_CF <= 0)



##Now we have to create the variables for the regression
## We create each of the new variable columns and use the "winsorize" command of the DescTools package, which needs to be installed first:
install.packages("DescTools")
library(DescTools)


##ln_IK_0
Orig.Data$IK_0 <- (-Orig.Data$IQ_CAPEX/Orig.Data$IQ_NPPE)
Orig.Data$IK_0 <- Winsorize(Orig.Data$IK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- mutate(Orig.Data, ln_IK_0 = log((IK_0)+1))


#ln_ProfitsK_0
Orig.Data$ProfitsK_0 <- Orig.Data$IQ_OPER_INC/Orig.Data$IQ_NPPE
Orig.Data$ProfitsK_0 <- Winsorize(Orig.Data$ProfitsK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  mutate(ln_ProfitsK_0 = ifelse((ProfitsK_0) > 0, log((ProfitsK_0)+1), -log(1-(ProfitsK_0))))
## Note: this action produces some NaNs, when Operating Income/NPPE + 1 goes below 0 (since ln(-x) returns an error). Therefore we replace NaNs with NAs.
Orig.Data$ln_ProfitsK_0[is.nan(Orig.Data$ln_ProfitsK_0)] <- NA


##ln_SalesK_0
Orig.Data$SalesK_0 <- Orig.Data$IQ_REV/Orig.Data$IQ_NPPE
Orig.Data$SalesK_0 <- Winsorize(Orig.Data$SalesK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_SalesK_0 = log((SalesK_0)+1)) %>%
  ungroup()
```

```
## TOBINS Q (market value over book value) NOT SOLVED

##ln_Q_0
Orig.Data$Q_0 <- (Orig.Data$IQ_MARKETCAP_average +
Orig.Data$IQ_TOTAL_LIAB)/Orig.Data$IQ_TOTAL_ASSETS
Orig.Data$Q_0 <- Winsorize(Orig.Data$Q_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_Q_0 = log(Q_0+1)) %>%
  ungroup()

##ln_LongDebtK. NB: no lag for this variable
Orig.Data$LongDebtK <- Orig.Data$IQ_LT_DEBT/Orig.Data$IQ_NPPE
Orig.Data$LongDebtK <- Winsorize(Orig.Data$LongDebtK, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- mutate(Orig.Data, ln_LongDebtK = log((LongDebtK)+1))

##ln_IntExpK_0
Orig.Data$IntExpK_0 <- -Orig.Data$IQ_INTEREST_EXP/Orig.Data$IQ_NPPE
Orig.Data$IntExpK_0 <- Winsorize(Orig.Data$IntExpK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_IntExpK_0 = log((IntExpK_0)+1)) %>%
  ungroup()

#ln_IntIncK_0
Orig.Data$IntIncK_0 <- Orig.Data$IQ_INTEREST_INCOME/Orig.Data$IQ_NPPE
Orig.Data$IntIncK_0 <- Winsorize(Orig.Data$IntIncK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_IntIncK_0 = log((IntIncK_0)+1)) %>%
  ungroup()

#ln_DivK_0
Orig.Data$DivK_0 <- -Orig.Data$IQ_TOTAL_DIV_PAID_CF/Orig.Data$IQ_NPPE
Orig.Data$DivK_0 <- Winsorize(Orig.Data$DivK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_DivK_0 = log((DivK_0)+1)) %>%
  ungroup()

#ln_StkIssueK_0
Orig.Data$StkIssueK_0 <- (Orig.Data$IQ_COMMON_ISSUED +
Orig.Data$IQ_PREF_ISSUED)/Orig.Data$IQ_NPPE
Orig.Data$StkIssueK_0 <- Winsorize(Orig.Data$StkIssueK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_StkIssueK_0 = log((StkIssueK_0)+1)) %>%
  ungroup()

#ln_StkRepK_0
Orig.Data$StkRepK_0 <- (-(Orig.Data$IQ_COMMON_REP +
Orig.Data$IQ_PREF_REP)/Orig.Data$IQ_NPPE)
Orig.Data$StkRepK_0 <- Winsorize(Orig.Data$StkRepK_0, probs=c(0.005,0.995), na.rm=TRUE)
```

```
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_StkRepK_0 = log(StkRepK_0+1)) %>%
  ungroup()
## Note: this action produces some NaNs, so we replace NaNs with NAs:
Orig.Data$ln_StkRepK_0[is.nan(Orig.Data$ln_StkRepK_0)] <- NA


#ln_NetDebtIssueK_0
Orig.Data$NetDebtIssueK_0 <-
((Orig.Data$IQ_TOTAL_DEBT_ISSUED+Orig.Data$IQ_TOTAL_DEBT_REPAID)/Orig.Data$IQ_NPPE)
Orig.Data$NetDebtIssueK_0 <- Winsorize(Orig.Data$NetDebtIssueK_0, probs=c(0.005,0.995),
na.rm=TRUE)
Orig.Data <- mutate(Orig.Data,ln_NetDebtIssueK_0 = ifelse( (NetDebtIssueK_0) > 0,
log((NetDebtIssueK_0)+1), -log(1-(NetDebtIssueK_0)) ))
## Note: this action produces some NaNs, replace NaNs with NAs:
Orig.Data$ln_NetDebtIssueK_0[is.nan(Orig.Data$ln_NetDebtIssueK_0)] <- NA



#ln_IntFinK_0
Orig.Data$IntFinK_0 <-  (Orig.Data$IQ_CASH_ST_INVEST/Orig.Data$IQ_NPPE)
Orig.Data$IntFinK_0 <- Winsorize(Orig.Data$IntFinK_0, probs=c(0.005,0.995), na.rm=TRUE)
Orig.Data <- Orig.Data %>%
  group_by(Company_Name) %>%
  mutate(ln_IntFinK_0 = log((IntFinK_0)+1)) %>%
  ungroup()
```

Now we split the dataset into small and large firms based on 'IQ_TOTAL_ASSETS'

```
## thereto we take the median per year and then split database by the largest and smallest firms each year.

## create list of years
lists.years <-  sort(unique(Orig.Data$year))

##create empty list (medyearly) and fill with median value for each year, using for loop
medyearly = c()

for (x in lists.years) {
  medyearly <- c(medyearly, median(Orig.Data$IQ_TOTAL_ASSETS[Orig.Data$year == x], na.rm =
TRUE))
}

#We create dataframe with A = year and B = median assets
Orig.Data.medyearly <- do.call(rbind, Map(data.frame, A=lists.years, B=medyearly))
colnames(Orig.Data.medyearly) <- c("year", "MedAssetsyearly")
view(Orig.Data.medyearly)

#We now add median values to main dataframe

Orig.Data <- merge(Orig.Data, Orig.Data.medyearly, by.x='year', by.y='year')

#Then we split dataframes according to whether their assets are higher or lower than the median

Orig.Data.small <- Orig.Data %>% filter(IQ_TOTAL_ASSETS <= MedAssetsyearly )
Orig.Data.large <- Orig.Data %>% filter(IQ_TOTAL_ASSETS > MedAssetsyearly )
```

##Running the regressions - Financialisation Model ------------------

##The GMM estimator is provided by the pgmm function. It's main argument is a dynformula which describes the variables of the model and the lag structure.

```
## PGMM with all firms
Model.All.Firms <- pgmm(ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
dplyr::lag(ln_SalesK_0)+
        dplyr::lag(ln_Q_0) +ln_LongDebtK + dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) +
        dplyr::lag(ln_DivK_0) + dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) +
        dplyr::lag(ln_NetDebtIssueK_0) +
        dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data=Orig.Data, model="twosteps", ef-
fect="twoways", index=c("Company_Name", "year"), transformation = 'd')
summary(Model.All.Firms)


## PGMM with large firms
Model.large.Firms <-pgmm(ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
dplyr::lag(ln_SalesK_0)+
        dplyr::lag(ln_Q_0) +ln_LongDebtK + dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) +
        dplyr::lag(ln_DivK_0) + dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) +
        dplyr::lag(ln_NetDebtIssueK_0) +
        dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data=Orig.Data.large, model="twosteps",
effect="twoways", index=c("Company_Name", "year"), transformation = 'd')
summary(Model.large.Firms)


## PGMM with small firms
Model.small.Firms <-pgmm(ln_IK_0 ~ dplyr::lag(ln_IK_0) + dplyr::lag(ln_ProfitsK_0) +
dplyr::lag(ln_SalesK_0)+
        dplyr::lag(ln_Q_0) +ln_LongDebtK + dplyr::lag(ln_IntExpK_0) + dplyr::lag(ln_IntIncK_0) +
        dplyr::lag(ln_DivK_0) + dplyr::lag(ln_StkIssueK_0) + dplyr::lag(ln_StkRepK_0) +
        dplyr::lag(ln_NetDebtIssueK_0) +
        dplyr::lag(ln_IntFinK_0) | dplyr::lag(ln_IK_0, 2:99), data=Orig.Data.small, mod-
el="twosteps", effect="twoways", index=c("Company_Name", "year"), transformation = 'd')
summary(Model.small.Firms)
```

VII. References

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