Graduate School of Decision Sciences

Universität Konstanz

GSDS
Working Paper
No. 2017-03

Foundation Owned Firms - A Detailed Decomposition of Differences in Return Distributions

Matthias Draheim
Phillip Heiler

February 2017

Graduate School of Decision Sciences

All processes within our society are based on decisions – whether they are individual or collective decisions. Understanding how these decisions are made will provide the tools with which we can address the root causes of social science issues.

The GSDS offers an open and communicative academic environment for doctoral researchers who deal with issues of decision making and their application to important social science problems. It combines the perspectives of the various social science disciplines for a comprehensive understanding of human decision behavior and its economic and political consequences.

The GSDS primarily focuses on economics, political science and psychology, but also encompasses the complementary disciplines computer science, sociology and statistics. The GSDS is structured around four interdisciplinary research areas: (A) Behavioural Decision Making, (B) Intertemporal Choice and Markets, (C) Political Decisions and Institutions and (D) Information Processing and Statistical Analysis.

GSDS – Graduate School of Decision Sciences
University of Konstanz
Box 146
78457 Konstanz

Phone: +49 (0)7531 88 3633
Fax: +49 (0)7531 88 5193
E-mail: gsds.office@uni-konstanz.de

-gsds.uni-konstanz.de

ISSN: 2365-4120
February 2017

Foundation Owned Firms - A Detailed Decomposition of Differences in Return Distributions

Matthias Draheim[†]

Phillip Heiler[‡]

February 13, 2017

We study if and how differences in firm policies have an impact on differences in return on assets of foundation owned firms (FoFs) and other firms (Nons) in Germany. We perform the analysis for return differences at the mean and at several quantiles. We document that for high-performing FoFs and Nons the return on asset difference is more pronounced in favor of Nons, for low-performing firms the difference vanishes. Performance differences are substantially driven by differences in firm policies. We find that (1) lower risk in FoFs increases FoF underperformance at high quantiles, but offsets it at low quantiles, (2) a lower leverage of FoFs offsets FoF underperformance at low quantiles and the median, (3) higher labor intensity in FoFs offsets their underperformance at low quantiles, (4) the larger size of FoFs increases FoF underperformance for the mean and all quantiles, (5) lower growth rates of FoFs increase FoF underperformance at high quantiles, and (6) residual differences beyond firm policies tend to be insignificant.

[*]University of Konstanz, Department of Economics, matthias.draheim@uni-konstanz.de

[†]University of Konstanz, Graduate School of Decision Sciences, phillip.heiler@uni-konstanz.de

Contents

List of Figures

List of Tables

1. Introduction

In Germany, Denmark, and Sweden big firms like Aldi, Bosch, Carlsberg, IKEA, and ThyssenKrupp are important players. They have in common that they are owned by a foundation. Foundations are legal entities without owners. They act and operate in line with the charter set up by the founder. For example, profit payments of foundation owned firms (FoFs) to the owner foundation have to be spent for purposes defined in the charter. The beneficiaries of charitable foundations are charitable projects and programs, those of family foundations are members of the founder's family. Hence, in contrast to other profit-oriented firms, there are fewer or no natural persons being residual claimants in FoFs. Traditional agency theory suggests that strong corporate governance of residual claimants is required for a firm to be viable in the long run; natural persons as owners with a strong profit motive are likely to push the management for high profits. If they are absent, other stakeholders might exploit the firm for their own benefits which could weaken financial performance and endanger the existence of the firm in the long run. Interestingly, many examples and several studies of FoFs show that they are clearly viable.

This study investigates how FoFs and firms that are not owned by a foundation (Nons) differ in terms of their financial performance, measured by returns on assets. We use accounting information of German firms to decompose the return distributions for 109 FoFs and about 11000 Nons. For a meaningful analysis, Nons are selected such that their firm policies are similar to those of FoFs; in our case, we remove firms having at least one firm policy variable being smaller than the FoFs' minimum or larger than the FoFs' maximum for that variable. In addition, we account for industry fixed effects in most of our models. Using the method of Rothe (2015), we isolate the impact of relevant firm policies on the difference in returns. In contrast to established decomposition methods by Blinder (1973) and Oaxaca (1973)[1], the method allows for analyzing return differences at different quantiles and not only at the mean and is robust with respect to nonlinear data generating processes and hence able to capture more observable heterogeneity than a simple linear mean model. In contrast to quantile regression methods or sequential decompositions, the effects of the analyzed variables add up to the overall return differ-

[1]The decomposition of Blinder (1973) and Oaxaca (1973) is a special case of the method of Rothe (2015), see Section 2.

ence of FoFs and Nons when using the Rothe (2015) method. In addition, we address the problem of a potential simultaneity bias that is adherent when using accounting data. We give a detailed discussion on how parameter estimates in a linear framework can be misleading if contemporaneous accounting information is used for estimation. Our identification approach exploits persistence of firm variables to obtain the actual determinants of return differences or at least absolutely lower bounds depending on the type of variable considered and degree of persistence over time. In addition to prior studies such as Draheim and Franke (2015), the paper contains a fully conditional analysis that considers all potential firm policy variables that affect returns simultaneously which goes beyond simple component-wise group comparisons.

Comparing the mean and quantiles of returns, we find pronounced return differences for the mean and high quantiles, where the returns of FoFs are significantly lower. A substantial proportion of the observed return differences at several quantiles can be attributed to differences in firm policies. We find that (1) lower risk in FoFs, as measured by the standard deviation of return on assets, increases FoF underperformance at high quantiles, but offsets it at low quantiles, (2) a lower leverage of FoFs offsets FoF underperformance at low quantiles and the median, (3) higher labor intensity in FoFs offsets FoF underperformance at low quantiles, (4) the larger size of FoFs increases FoF underperformance for the mean and all quantiles, (5) lower operating revenue growth rates of FoFs increase FoF underperformance at high quantiles, and (6) residual differences beyond firm policies tend to be insignificant.

Reasons for differences in firm policies and financial performance of FoFs and Nons are manifold. One important driver may be the profit motive that appears to be weaker in FoFs due to the lack of natural persons as residual claimants. In addition, most foundation charters support a stable development of the foundation's wealth and long-term orientation in FoFs. Therefore, managers may be less incentivized to generate profits by taking higher risks, but to pursue stable firm policies. This might explain lower returns of FoFs at a lower return volatility. In particular, this seems to hold for high quantiles of return on assets, see (1). A high equity buffer might serve as protection against economic downturns; FoFs tend to have a lower leverage. Apparently, a lower leverage in FoFs might translate into more freedom of action with respect to investments, in contrast to a potential shortage of funds in Nons due to high leverage (Myers (1977)). In line with that, we find that a lower leverage is beneficial for FoFs, in particular at lower return quantiles, see (2). Labor intensity appears to be higher in FoFs. We find pronounced substitution of raw material by labor in FoFs. Surprisingly, this seems to be beneficial for FoFs at low return quantiles, see (3). Only successful entrepreneurs usually transform their firms into an FoF. Thus, FoFs tend to be large, already when they are set up. We find that they are much larger than Nons. Small firms are usually more dynamic and react faster to changes in the market environment. Consistently, we find that the bigger size of FoFs contributes to underperformance over the whole return distribution, see (4). Possibly due to more long-term orientation that favors more conservative strategies, operating revenue growth rates in FoFs tend to be lower. This seems to explain underperformance of FoFs, in particular at high quantiles, see (5). We find that differences in these policies can explain a substantial proportion of return differences over the whole distribution, see (6).

Several studies compare the financial performance of Danish FoFs to different control samples. Thomsen (1996) uses the largest 150 Danish Nons, Thomsen (1999) uses Nons listed at the Copenhagen Stock Exchange, and Thomsen and Rose (2004) use Danish Nons with dispersed ownership or family control as benchmarks. All studies find that the financial performance of Danish FoFs is not inferior. Thomsen and Hansmann (2013) find that financial performance of FoFs improves if there is less personal overlap between the boards of the foundations and those of the corresponding FoFs, more outside ownership, and more administrative independence of foundations and FoFs. For Germany, Herrmann and Franke (2002) compare FoFs to German firms being listed at a stock exchange. They find that FoFs perform even slightly better. In addition, labor intensity is higher in FoFs. Draheim and Franke (2015) analyze a larger sample of German FoFs. Additionally, they control for different institutional setups of FoFs. They find that, relative to control firms, FoFs are more conservative in terms of financing policy, they are more labor-intensive, their financial performance, measured by return on assets, is lower; their risk, measured by the standard deviation of returns on assets, is also lower. As a consequence, risk-adjusted financial performance of FoFs is not significantly different from Nons. We add to the literature by decomposing the return differences of FoFs and Nons at several quantiles.

We attribute a substantial proportion of these differences to differences in firm policies that Draheim and Franke (2015) identify. It turns out that the impact of these policies varies when comparing top-, average- and low-performers.

The paper is structured as follows. In the next section, there is an overview over the relevant decomposition methods. Then, we discuss identification and simultaneity issues. Estimation and inference are addressed in the subsequent section. Then, the following section describes the data. Observational findings are shown in the subsequent section. After reporting and discussing decomposition results, the paper concludes.

2. Decomposition Methods

Since the seminal work of Blinder (1973) and Oaxaca (1973) decomposition methods of distributional features from non-overlapping groups have been heavily used in economics. The literature on labor market or education outcomes decomposes differences in wages or test scores between two groups such as genders, time periods, or migrants and natives. It is the objective to investigate whether differences of an outcome variable are due to differences of explanatory variables, such as the level of education in the context of wage analyses, and the magnitude of these variables. Here, we are particularly interested in differences in the financial performance measured by the return on assets between FoFs and Nons.

For two groups $g = 0, 1$, a simple linear mean model for the return on assets, denoted by Y_i^g, within groups is given by

$$Y_i^g = X_i^{g\prime}\beta^g + \varepsilon_i^g \tag{2.1}$$

assuming an error orthogonal to the regressors, Y_i^g being the return of firm i belonging to group g and X_i^g being a vector of firm-specific covariates such as financing policies or size measures. Using this model, one can decompose the difference in the mean outcomes between group 0 and 1 as follows

$$
\begin{aligned}
E[Y_i^1] - E[Y_i^0] &= E[X_i^1]\beta^1 - E[X_i^0]\beta^0 \\
&= \underbrace{E[X_i^1](\beta^1 - \beta^0)}_{\Delta_S^\mu \text{"Structure effect"}} + \underbrace{(E[X_i^1] - E[X_i^0])\beta^0}_{\Delta_X^\mu \text{"Composition effect"}}.
\end{aligned}
$$

The two components of the decomposition are also referred to as price or discrimination and endowment effect, respectively. This aggregate decomposition can yield insights into the overall contribution of differences in firm policies to differences in financial performance. To get the separate effect of each policy variable, the composition effect can be decomposed as follows

$$\Delta_X^\mu = \sum_{k=1}^{K} (E[X_{ik}^1] - E[X_{ik}^0])\beta_k^0 \tag{2.2}$$

with each element within the summation representing the marginal impact of the k-th covariate on the aggregate composition effect. Computing a detailed decomposition at the mean is labeled a solved problem in the literature (Fortin et al. (2011)). Its solution does not depend on the ordering of the covariates and adds up to the total effect.

For quantiles and distributional features other than the mean, the analysis is inherently difficult since they are no longer additive separable functions in the population defining parameters, in contrast to the mean function. Consequently, sequential detailed decompositions are widely used (DiNardo et al. (1995), Machado and Mata (2005), Altonji et al. (2012), Chernozhukov et al. (2013)). Their general idea is to first get an estimate for the contribution of a single variable to the aggregate decomposition and then conditional on the first variable for a subsequent one and so forth leading to an overall *path dependent* decomposition. This is an unattractive feature and in many examples these path-wise decompositions are strongly varying across different orderings. Another approach is based on local approximations of the differences via recentered influence function regressions (Firpo et al. (2007), Firpo et al. (2013)). They tend to be inaccurate if the compared distributions are not close to location shifted versions of each other or if their differences are generally large.

Rothe (2015) proposes a more general decomposition for one-dimensional distributional features such as quantiles or standard deviations. He relies on a copula approach to rewrite the joint distribution function of the explanatory variables as a continuous function of marginal distributions only which eases the construction of counterfactual distributions. His approach gives a *path independent* detailed decomposition of the composition effect into three different components: changes in marginal distributions, interactions, and a difference in the dependence structure of the explanatory variables across groups.

Formally, for two groups $g = 0, 1$, let F_Y^g and F_X^g be the distribution functions for outcome Y and covariates X with support $\mathcal{Y}^g$ and $\mathcal{X}^g$ and the conditional cumulative distribution function be $F_{Y|X}^g$. A distributional feature of interest $v(F)$ is a functional such that $v : \mathcal{F} \to \mathbb{R}$ maps from all one-dimensional distribution functions to the real numbers such as the mean or a quantile. The overall difference for a functional v between two group outcomes Δ_O^v is then given by

$$\begin{aligned}\Delta_O^v &= v(F_Y^1) - v(F_Y^0) \\ &= \underbrace{(v(F_Y^1) - v(F_Y^{0|1}))}_{\Delta_S^v \text{"Structure Effect"}} + \underbrace{(v(F_Y^{0|1}) - v(F_Y^0))}_{\Delta_X^v \text{"Composition Effect"}}\end{aligned}$$

with

$$F_Y^{0|1}(y) = \int F_{Y|X}^0(y, x) dF_X^1(x) \tag{2.3}$$

being a *counterfactual* distribution that uses the conditional distribution of the outcome given observables as in group zero but the joint distribution of the explanatory variables as in group one. This corresponds to a hypothetical distribution that could be observed for group one if the observations became part of the zero group. We impose $\mathcal{X}^1 \subset \mathcal{X}^0$ to assure that the integral in (2.3) is well-defined or put differently that the range of firm policy variables are overlapping and hence comparable across groups. For further related identification assumptions see the subsequent section.

To get a detailed decomposition Rothe proposes to rewrite (2.3) in terms of the single marginal distributions. By Sklar's Theorem (Sklar (1959)) for continuously distributed variables there exists a unique function $C_g(\cdot)$ called coupla such that

$$F_X^g(x) = C^g(F_{X_1}^g(x_1), \ldots, F_{X_d}^g(x_d)) \text{ for } g \in \{0,1\}.$$

The copula is effectively a multivariate cumulative distribution function with standard uniformly distributed marginals. For a short example on why the copula can be helpful for a general decomposition, consider the case of two covariates, i.e., $K = 2$. By adding and subtracting, one can rewrite the composition effect as follows

$$\begin{aligned}
\Delta_X^v =& v\Big(\int F_{Y|X}^0(y,x)dC^1(F_{X_1}^1(x_1), F_{X_2}^1(x_2))\Big) \quad + v\Big(\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^1(x_1), F_{X_2}^1(x_2))\Big) \\
& \underbrace{- v\Big(\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^1(x_1), F_{X_2}^1(x_2))\Big)}_{\Delta_D^v \text{"Dependence Effect"}} \quad \underbrace{- v\Big(\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^0(x_1), F_{X_2}^0(x_2))\Big)}_{\beta^v(1,1)}.
\end{aligned}$$

Note that the dependence effect uses the same marginal and conditional distributions and hence is only affected by differences between the copula functions of the two groups which can be interpreted as a difference in the dependence structure of the covariates across the two groups. By adding and subtracting, the second component on the right hand side can further be rewritten as

$$\begin{aligned}
\beta^v(1,1) =& v\Big(\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^1(x_1), F_{X_2}^0(x_2))\Big) - v(F_Y^0) && \Rightarrow \Delta_M^v(1,0) \\
&+ v\Big(\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^0(x_1), F_{X_2}^1(x_2))\Big) - v(F_Y^0) && \Rightarrow \Delta_M^v(0,1) \\
&+ \left.\begin{aligned}
&\Big[v\Big(\textstyle\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^1(x_1), F_{X_2}^1(x_2))\Big) - v(F_Y^0) \\
&-v\Big(\textstyle\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^1(x_1), F_{X_2}^0(x_2))\Big) - v(F_Y^0) \\
&-v\Big(\textstyle\int F_{Y|X}^0(y,x)dC^0(F_{X_1}^0(x_1), F_{X_2}^1(x_2))\Big) - v(F_Y^0)\Big]
\end{aligned}\right\} && \Rightarrow \Delta_M^v(1,1)
\end{aligned}$$

with $\Delta_M^v(\mathbf{k})$ reflecting the direct contribution of a possibly simultaneous change of the covariates defined by $\mathbf{k} \in \{0,1\}^K$. For the first component $\Delta_M^v(1,0)$ note that it can only be driven by a change of the marginal distribution of the first covariate X_1 of group zero to $F_X^1(x_1)$ while conditional distribution, copula, and remaining marginal distributions are being held fixed. This corresponds to a fixed partial distributional policy effect Rothe (2012). $\Delta_M^v(0,1)$ can be interpreted similarly while $\Delta_M^v(1,1)$ is the difference due to a joint change in the marginal of both covariates minus the individual marginal contributions $\Delta_M^v(1,0)$ and $\Delta_M^v(0,1)$ which can be interpreted as a pure interaction effect.

For the general case, one can rewrite the composition effect in a similar fashion as

$$\Delta_X^v = \sum_{i \leq |\mathbf{k}| \leq K} \Delta_M^v(\mathbf{k}) + \Delta_D^v$$

with $|\mathbf{k}| = \sum_{i=1}^{K} \mathbf{k}_i$. The components $\Delta_M^v(\mathbf{k})$ can capture either direct contribution of a change in the marginal distribution of a variable to the overall difference, i.e., $\mathbf{k}$ being the corresponding unit vector or contributions of interaction terms.

The difference in the copulas or the dependence structure Δ_D^v is a new component that is not addressed by prior decomposition methods. In the context of firm accounting data we would expect this effect to be close to zero since the stochastic relation of fundamental firm data taken from balance sheet information is unlikely to differ based on whether the firm is owned by a foundation or other shareholders.

3. Identification and Simultaneity Bias

The use of accounting information for achieving causal statements is inherently difficult since, by construction, any double-entry bookkeeping system creates dependencies over the different accounting figures that are not one-directional. From a corporate governance point of view, a management has different channels to influence the company's accounting figures. This is the so-called (real) earnings management. There are many examples that show that there are interdependencies of accounting figures. For instance, a balance sheet contraction without changing the equity capital lowers leverage which is defined as debt divided by total assets and raises return on assets. A firm can do so by selling receivables, so-called factoring. Another example is that a firm's management might have a target leverage ratio. On the other hand, Welch (2004) finds that stock returns can explain a substantial proportion of leverage dynamics. Also, a firm that is particularly indebted to its employees might be interested in publishing high personnel expense ratios on a regular basis. Thus, such a firm might be willing to earn lower returns and get more employees' satisfaction instead. There are many more examples showing that potentially everything depends on everything when dealing with accounting data.

For illustration, consider the following linear model setup. Let Y_{it} be the return on assets, X_{it} the standard deviation of the return on assets, and Z_{it} the leverage of firm i in year t. In the following, we impose without loss of generality that all variables have a mean of zero. For simplicity, assume all firms are observed over the time period $t = 1, \ldots, T$. Let the structural mechanism be described by the following model

$$
\begin{aligned}
Y_{it} &= X_{it}\beta + Z_{it}\gamma + \varepsilon_{it}, \\
Z_{it} &= X_{it}\alpha + Y_{it}\delta + u_{it}
\end{aligned}
$$

with all errors being orthogonal to the contemporaneous X_{it} and not correlated across equations. The latter assumption could be easily relaxed. In the data at hand, the risk measure is unobservable on a yearly basis but a standard deviation of the return on assets can be computed ex post and used as an average measure of risk. The model averaging all variables within firm over time looks as follows

$$
\begin{aligned}
\bar{Y}_i &= \bar{X}_i\beta + \bar{Z}_i\gamma + \bar{\varepsilon}_i, \\
\bar{Z}_i &= \bar{X}_i\alpha + \bar{Y}_i\delta + \bar{u}_i.
\end{aligned}
$$

Assume we are interested in the structural parameters of the first equation. Ignoring the simultaneity of Z_{it} and Y_{it}, we could run an OLS regression for the first equation. One can show that the estimators for β and γ do not converge to the true parameters, i.e., under some mild regularity conditions it holds that

$$
\begin{aligned}
\hat{\beta} &\xrightarrow{p} \frac{\beta + \alpha\gamma}{1 - \delta\gamma} + \left[\frac{\rho_{X,Z}}{\sigma_X \sigma_Z}\right] \frac{\gamma\sigma_u^2 + \delta\sigma_\varepsilon^2}{(1 - \rho_{X,Z}^2)(1 - \delta\gamma)^2} \\
\hat{\gamma} &\xrightarrow{p} \frac{\gamma\sigma_u^2 + \delta\sigma_\varepsilon^2}{(1 - \rho_{X,Z}^2)\sigma_Z^2(1 - \delta\gamma)^2}
\end{aligned}
$$

assuming that $(1 - \delta\gamma) \neq 0$, $|\rho_{XZ}| < 1$ with σ_L^2 being the variance of a random variable L, $\sigma_{L,S}^2$ the covariance between two random variables L and S, and $\rho_{L,S}$ their correlation coefficient. All formal statements for the assumptions as well as proofs and derivations can be found in Appendix A.

Hence, depending on the type of simultaneity that is determined by the signs and size of the parameters, we would over- or underestimate the true structural relationships in a nontrivial fashion. To overcome this issue, we propose to exploit the persistence of firm policy variables as an identification strategy. In particular for leverage ratios, Lemmon et al. (2008) and Hanousek and Shamshur (2011) find historically strong persistence even over several decades. Assume leverage can be observed in a year $t = 0$ prior to the period for which we average the return on assets. To put persistence into a model, say that the dynamics of leverage are appropriately captured by a stationary AR(1) structure, i.e., we have that

$$Z_{it} = \theta Z_{it-1} + \nu_{it} \Leftrightarrow Z_{it} = Z_{i0}\theta^t + \sum_{j=0}^{t-1} \theta^j \nu_{it-j}$$

with ν_{it} being some independent zero mean error. This could be easily relaxed and merely serves illustrative purposes. Taking averages for the leverage over $t = 1, \ldots, T$ yields

$$\begin{aligned} \bar{Z}_i &= Z_{i0}\frac{1}{T}\sum_{t=1}^{T}\theta^t + \frac{1}{T}\sum_{t=1}^{T}\sum_{j=0}^{t-1}\theta^j \nu_{it-j} \\ &\equiv Z_{i0}\Theta + N_i. \end{aligned}$$

Using the lagged leverage as regressor, leads to the following model

$$\bar{Y}_i = \bar{X}_i\beta + Z_{i0}\omega + \mu_i$$

with $\mu_i = \bar{Z}_i\gamma - Z_{i0}\omega + \bar{\varepsilon}_i$. Assuming that simultaneity is not present across different time periods, one can show that OLS for this model yields

$$\begin{aligned} \hat{\beta} &\xrightarrow{p} \beta, \\ \hat{\omega} &\xrightarrow{p} \Theta\gamma \end{aligned}$$

and, hence, we can consistently estimate the structural parameter on the standard deviation of the return on assets. Under stationarity, we have that $|\Theta| < 1$ and, thus, our estimated coefficient for the leverage, $\hat{\omega}$, would correspond to a lower bound in absolute terms for the actual structural parameter γ. Since for leverage the AR parameter is expected to be positive, our estimates can be understood as actual lower bounds for the structural relationship. The higher the persistence in the variable, the closer the estimates are to the true parameter. In particular, $\hat{\omega}$ converges to γ if the firm policy variable follows a random walk, i.e., $Z_{it} = Z_{it-1} + \nu_{it}$.

This allows in a similar fashion for identification of the actual components or at least the lower bounds of the detailed decomposition in equation (2.2). We are aware that, for the linear model, applying the decomposition on an IV (instrumental variables) estimator, that uses the lagged policy variable as instrument, would in general be a better way how to approach the problem for the average return difference. However, the main focus of this study is the heterogeneity between low-, average-, and top-performers and, hence, the Blinder-Oaxaca decomposition serves more as a benchmark comparison to the Rothe decomposition for which the IV methodology cannot be transferred as easily as for conditional mean models.

Note that our approach can be regarded as a predictive problem as well. For instance, assume at the end of time $t = 0$ a manager would like to predict the possible effect for the next year(s) of adjusting a firm policy towards the policy of competing FoFs in the market. She can only observe her firm's and the competing firms' policy variables right now but not for the following periods. Since her decision is based on the information set in time 0, understanding the relationship between structural parameters and the actually available information can be beneficial. Using the biased results from a least squares regression for contemporaneous variables would be misleading since the estimates do not reflect the relation between today's firm policy variables and future returns. Thus, in this study, we rely on the assumption of persistence of certain firm policy variables. For instance, we assume that the leverage of today can be seen as a good proxy for the leverage of tomorrow which also appears to be backed by the literature. We use this to predict future returns. So, the manager can analyze whether an adjustment of the firm's leverage towards the leverage of FoFs might have a desired impact on the firm's return on assets.

4. Estimation and Inference

All Blinder-Oaxaca based models are estimated via least squares using heteroscedasticity robust standard errors. For the copula decomposition, we need to estimate the marginal distribution functions of the covariates for each group, the copula, and the conditional distribution function within the control group. We mostly follow the proposals by Rothe (2015) and estimate the marginal distributions by the empirical distribution function, i.e.,

$$\hat{F}^g_{X_l}(x) = \frac{1}{n_g} \sum_{i=1}^{n_g} \mathbb{1}(X^g_{il} \leq x)$$

with n_g being the group size of group g. For the conditional distribution function, we use a parametric approach of distributional regression (Foresi and Peracchi (1995)) which assumes that locally at a point y, it holds that $F^g_{Y|X}(y, x) \equiv \Phi(x'\delta^g(y))$ with Φ being a strictly increasing, positive link function. Here, we use the standard normal distribution function. The parameters depend on the location of y and can be estimated by maximum likelihood, i.e.,

$$\hat{\delta}^g(y) = \arg\max_{\delta} \sum_{i=1}^{n_g} (\mathbb{1}(Y^g_i \leq y) \log(\Phi(X^{g\prime}_i \delta)) + (1 - \mathbb{1}(Y^g_i \leq y)) \log(1 - \Phi(X^{g\prime}_i \delta))).$$

Plugging in the estimate into the expression for the conditional distribution function gives the prediction. The detailed decomposition only requires estimation of the conditional distribution function for the 0 group which is very large in the data at hand. Hence, we allow for a more flexible model by including quadratic terms of all firms policy variables as well as first order interactions.

For the copula, we restrict attention to the Gaussian copula model only. This is beneficial since its parameterization requires the estimation of joint distributions for only two variables at once. Especially for estimating the copula for the FoFs with less than 110 observations, the possibly restrictive nature is required to still achieve precise estimates. Formally, assume that $C^g_\Sigma(u) = \Phi^K_\Sigma(\Phi^{-1}(u_1), \ldots, \Phi^{-1}(u_K))$ is a K-dimensional Gaussian copula with variance covariance matrix Σ. The parameterization of the copula can be done via a minimum distance approach that minimizes the squared distance between the estimated joint distribution of a pair of variables and the Gaussian copula, i.e., for a pair

a, b

$$\hat{\Sigma}_{ab} = \arg\min_{\rho} \sum_{i=1}^{n_g} (\hat{F}^g_{X_a,X_b}(X^g_{ia}, X^g_{ib}) - \Phi^2_\rho(\Phi^{-1}(\hat{F}^g_{X_a}(X^g_{ai})), \Phi^{-1}(\hat{F}^g_{X_b}(X^g_{bi}))))^2$$

with

$$\hat{F}^g_{X_a,X_b}(x_a, x_b) = \frac{1}{n_g} \sum_{i=1}^{n_g} \mathbb{1}(X^g_a \leq x_a, X^g_b \leq x_b).$$

Rothe (2015) shows that under some regularity conditions in all steps, the estimate for the marginal components $\hat{\Delta}^v_M(\mathbf{k})$ of the detailed decomposition is root n asymptotically normal. The standard errors are computed using a nonparametric bootstrap that samples with replacement.

5. Data

We analyze accounting data of German firms for the sampling period 2004 until 2013. Accounting data is provided by Orbis. For the identification of FoFs, we refer to a list from 2012 by Marc Eulerich (University of Duisburg/Essen) that is not publicly available. This list is an updated version of the list of German FoFs in Fleschutz (2009). It comprises 740 firms. For each of these firms, we check the ownership structure. A firm is included as an FoF, if a foundation has at least two percent of the voting rights of the firm or at least two percent of the equity stake of the firm. Robustness checks with a more restrictive threshold are considered in Section 7.4 as well. We consider effective shares of the foundation in the foundation owned firm since there are often pyramid structures (Draheim and Franke, 2015). For most FoFs, we get data on voting rights from Orbis. If the data is not available for a particular firm, we hand-collect it using firm reports. Concerning the equity stakes, most data is provided by Hoppenstedt. Again, we hand-collect data if Hoppenstedt does not provide the desired information. In this study, we compare FoFs to firms that are not foundation owned (Nons). For a meaningful comparison, we apply several criteria for the construction of Nons that are described below and in Section 7.1.

We start with the collection of all German firms available in Orbis. Several data filters are applied. We exclude firms that are not for-profit. For industry classification, we use two digit US SIC codes. We do not include financial institutions (US SIC 60-64) due to special accounting conventions or firms that are part of the public authority (US SIC 91-93, 97) because in this sector we assume incentive structures to be different from the other sectors we analyze. In order to avoid outliers due to structural breaks such as a mergers or acquisitions or due to data errors, we analyze the time series of operating revenue, total assets, and the number of employees for each German firm available in Orbis. If we see a negative change of more than 50 percent or a positive change of more than 100 percent from one year to the next year, we exclude all the firm's observations (for each variable) before the most current change (Strebulaev and Yang (2013)). Similarly, if a firm switches from German accounting standards to IFRS or vice versa, then we exclude all the observations before the most current switch. All observations are deflated to the price level of 2004 using the Eurostat BIP deflator for Germany.

For our analysis, we require each firm to report operating revenue for at least two years within the sampling period 2004 to 2013. We denote the first year a firm reports operating revenue as t_0. In addition, we require each firm to report material expense, personnel expense, and shareholder funds at least for the year t_1. EBIT and total assets is required to be reported at least for the years t_2 and t_3. Thus, we require firms to report accounting figures for at least four years. All firms that do not meet these requirements are excluded. Firms that have missing values for any firm policy variable are disregarded as well. To avoid low persistence in the firm policy variables that would weaken the identification result according to Section 3, the age of the firms is required to be at least ten years, i.e., we exclude start-ups. This should remove extreme adjustments that are common in the first years of a firm. We consider only industries with both FoFs and Nons. That leaves us with 109 FoFs and 20260 Nons.

We use variables for our analysis that Draheim and Franke (2015) find to be significantly different for FoFs and Nons. Table 5.1 contains the description and construction of the variables we use.

Table 5.1: Description of Variables

Variable	Description	Time
RoA	Average return on assets = EBIT / total assets, financial performance measure.	$t_2 - t_{max}$
σ_{RoA}	Standard deviation of the RoA, risk measure.	$t_2 - t_{max}$
PPM	Personal expense / material expense, production policy measure.	t_1
Leverage	1 − (shareholder funds / total assets), financing policy measure.	t_1
OR rank	$[0, 1]$-normalized operating revenue rank relative to all other firms at time of entrance, size measure.	t_1
OR growth	Operating revenue growth, measure of growth dynamics	$t_0 - t_1$
HGB	Indicator for whether firm uses German accounting standards or IFRS	constant
Listed	Indicator for whether firm listed at stock exchange or not	constant
Voting share	Share of foundation's voting rights	constant
Charitable	Indicator for whether foundation charitable or not	constant

This table describes the construction of the relevant variables used in this study.

We are aware of the fact that we, in general, do not use all available accounting information for a firm; several variables (PPM, Leverage, OR rank) are only analyzed for one year as Table 5.1 indicates, although we likely observe them for more years. This is due to accounting for a potential simultaneity bias as explained in Section 3. There is always a trade-off between information content and avoiding a simultaneity bias when using accounting data. However, we think that we do not neglect too much information following our approach. Since operating revenue is very unstable over time, i.e., non-stationary, we use as size measure OR rank. This is defined as the rank according to the size of operating revenue (1 represents the smallest firm, N represents the largest firm at t_1) divided by N. OR rank turns out to be much more stable than operating revenue itself, i.e., OR rank is persistent by construction. According to literature, leverage is also found to be persistent (e.g., Lemmon et al. (2008) and Hanousek and Shamshur (2011)). PPM turns out to be less persistent than leverage but more presistent, relative to OR growth. As explained in Section 3, the estimated effects get closer to the true effects, the higher persistence is. Nonetheless, estimates can be interpreted as lower bounds although the according variable does not show high levels of persistence.

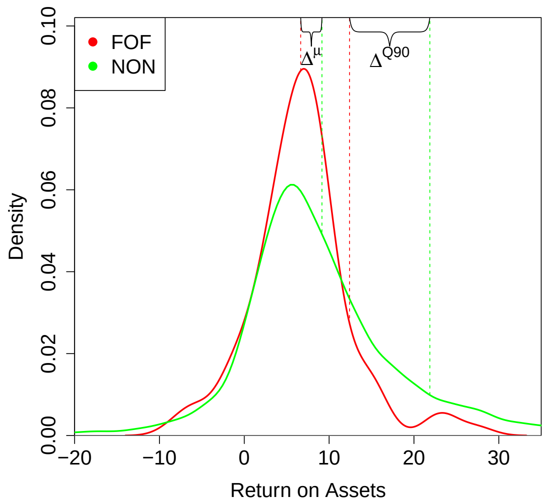
6. Observational Findings

Table 6.1: Untrimmed Sample Comparison

	FoF, n = 109					Non, n = 20260				
	Mean	SD	Q25	Median	Q75	Mean	SD	Q25	Median	Q75
RoA	6.650	5.792	3.608	6.689	9.169	9.132	11.663	3.444	7.496	13.395
σ_{RoA}	4.279	3.047	2.098	3.570	6.084	6.006	6.386	2.207	4.302	7.714
PPM	1.693	3.541	0.361	0.722	1.607	1.470	3.370	0.171	0.450	1.117
Leverage	0.630	0.210	0.460	0.675	0.778	0.722	0.284	0.567	0.742	0.881
OR rank	0.847	0.157	0.769	0.889	0.969	0.532	0.279	0.301	0.545	0.769
OR growth	0.068	0.135	-0.008	0.048	0.120	0.081	0.217	-0.032	0.053	0.161

This table shows summary statistics for the the return on assets (RoA) and firm policy variables for FoFs and Nons.

Figure 6.1: Density: Return on Assets



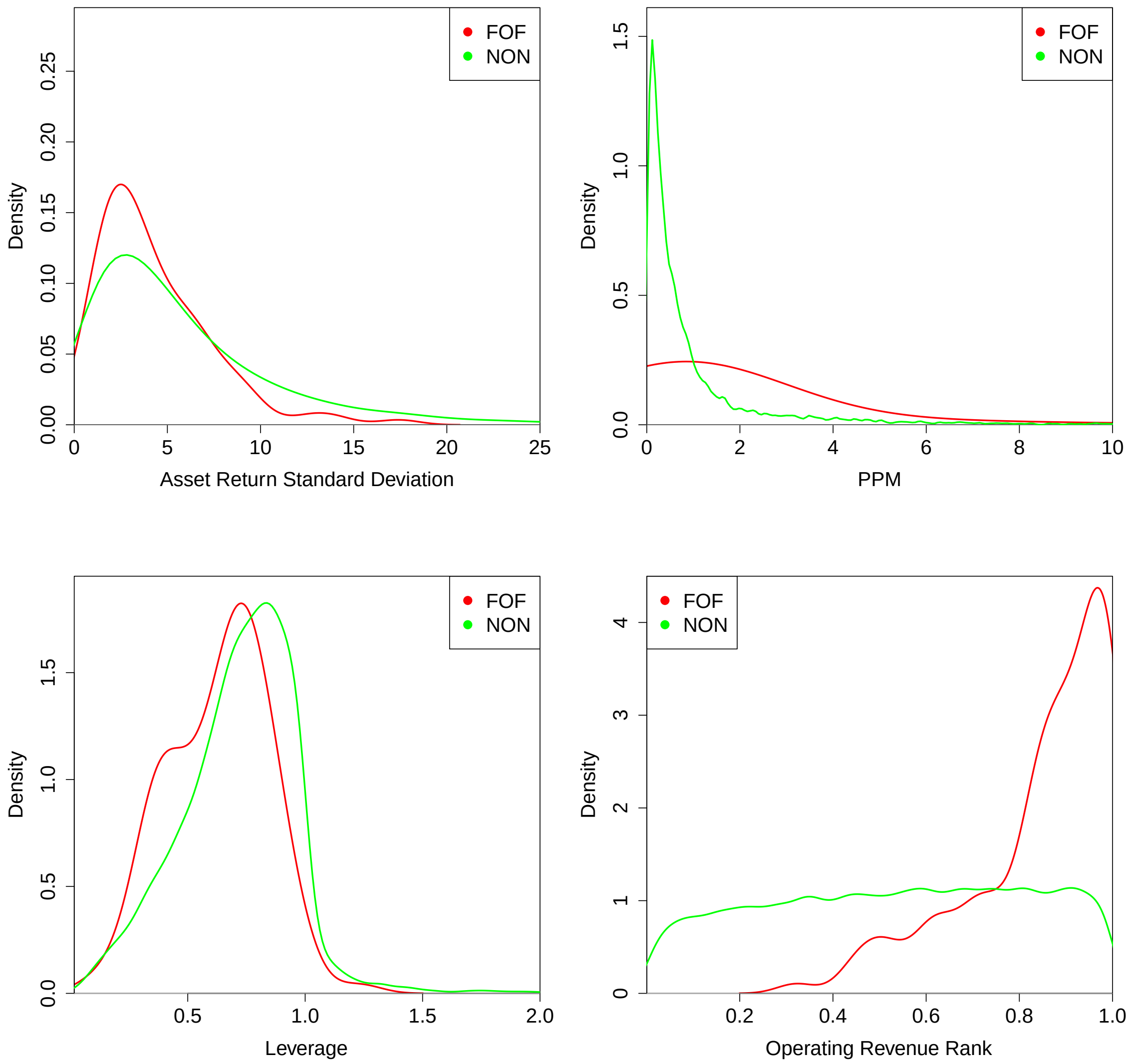
This figure shows kernel density estimates of the return on assets for FoFs and Nons. The estimates are obtained with a boundary corrected Epanechnikov kernel. Bandwidths are chosen via cross-validation.

Table 6.1 shows summary statistics for the most relevant variables of our analysis before any trimming procedure as done in Section 7. We report the mean, the standard deviation, the 25 percent quantile, the median, and the 75 percent quantile for each variable, separately for FoFs and Nons. We choose these values for the points at which we estimate the decompositions in Section 7 as well. Although results would be interesting for quantiles higher than the 75 percent quantile or lower than the 25 percent quantile, estimates at extreme quantiles are less reliable due to the small number of FoFs.

First, we consider the RoA, the outcome variable in this study, for FoFs and Nons. FoFs have a slightly higher 25 percent quantile RoA than Nons: 3.61 percent for FoFs and 3.44 for Nons. For the other quantiles as well as for the mean, the RoA is lower for FoFs. This difference seems to increase along the quantiles: the median RoA is 6.69 percent for FoFs and 7.50 percent for Nons, the 75 percent quantile RoA is 9.17 percent for FoFs and 13.40 percent for Nons. This is also depicted in Figure 6.1 which plots the RoA density function for FoFs and Nons[2]. The right tail of the density function contains more probability mass for Nons indicating more firms with high returns. As an illustration, the figure contains the return differences for the mean and the 90 percent quantile. It is very striking that the difference increases dramatically as we move to more extreme quantiles. This is one of the major motivations for a general decomposition that goes beyond the mean. A Kolmogorov-Smirnoff (KS) test on equality of the two cumulative distribution functions is rejected at $p < 0.001$.

[2]All density functions in Figure 6.1 and Figure 6.2 are estimated using a second order Epanechnikov kernel with cross-validated bandwidths.

Figure 6.2: Density: Firm Policy Variables



This figure shows kernel density estimates of σ_{RoA}, PPM, Leverage, and OR rank for FoFs and Nons. The estimates are obtained with a boundary corrected Epanechnikov kernel. Bandwidths are chosen via cross-validation.

Second, we consider several firm variables that might have an impact on the difference in RoA for FoFs and Nons. For σ_{RoA}, the picture is clear-cut. For all reported quantiles and the mean, σ_{RoA} is lower for FoFs. This difference seems to increase along the quantiles monotonically. Hence, the highest difference is for the 75 percent quantile: it is 6.08 percent for FoFs and 7.71 percent for Nons. Figure 6.2, upper left hand corner, displays the density function of σ_{RoA} for FoFs and Nons. For FoFs, there is more mass for low levels of σ_{RoA} and less mass for high levels of σ_{RoA}, relative to Nons. The findings for σ_{RoA} are consistent with the result that the standard deviation of RoA within the group of FoFs is 5.79 percent which is much lower than the standard deviation of RoA of Nons which is 11.66 percent. There is a lot of literature supporting the positive relation between risk and return of a firm, see, e.g., Glosten et al. (1993), Duffee (1995), and Bekaert and Wu (2000).

For all quantiles and the mean, labor intensity is higher in FoFs, as measured by PPM. The means for FoFs and Nons seem to be driven by some extremely labor intensive firms since they are higher than the 75 percent PPM quantiles. Figure 6.2, upper right hand corner, visualizes the finding of more labor intensity in FoFs. Draheim and Franke (2015) find that most FoFs are firms with former family ownership, i.e., family firms. Thus, FoFs share several characteristics with family firms. Chirico and Bau (2014) and Bingham et al. (2011) observe that there is a firm culture in family firms that benefits employees. More labor intensity is one channel to do so.

Leverage is consistently lower in FoFs. All reported quantities as well as Figure 6.2, lower left hand corner, support this finding. For low levels of leverage there is more mass for FoFs, while there is less mass for higher levels of leverage for FoFs. Smith (1977) argues that small firms face higher costs to issue new equity and to issue long-term debt. FoFs tend to be clearly larger than Nons (see OR rank). Thus, it is likely that Nons are more leveraged.

Summary statistics for the size, measured by OR rank, support the hypothesis that FoFs are much larger than Nons. All OR rank quantiles of FoFs are much higher than the quantiles of Nons. Figure 6.2, lower right hand corner, supports this. While the density function for Nons is flat which suggests a uniform rank distribution[3], there is a very pronounced peak at the right side of the density function for FoFs. Draheim and Franke (2015), who generate a nearest neighbor matching firm sample for 164 FoFs, match with respect to industry and size. They also find that FoFs are larger than control firms but, due to their matching approach, their observed discrepancy is not as strong as in our sample.

[3]This is the case by construction since Nons make up most of the sample. Note that the ranking of operating revenue is defined before any trimming procedure is applied and hence there are some slight deviations at the boundaries.

Concerning growth dynamics, we find that OR growth tends to be smaller for FoFs. Only for the 25 percent quantile, we find lower OR growth for Nons. This finding for FoFs and Nons might be in line with Evans (1987) who finds a negative relationship between firm growth and size.

For all variables considered here, the KS tests reject the null of equal distributions in the covariates for FoFs and Nons with p-values below 0.001. In the subsequent section, we address the question of whether and how these significant differences translate into financial performance differences.

7. Results

7.1. Model Setup

In this section, we present the results for the decompositions of RoA differences. The decompositions are performed by using the method of Blinder (1973) and Oaxaca (1973) (this method is denoted by "BO") and of Rothe (2015) (this method is denoted by "RO"). For both methods, we estimate 7 models whereas we regard model 2 and 3 as the baseline models; the other models are included as robustness checks. The models differ in how and if they take into account OR growth, industry fixed effects, accounting standards, stock listing effects, voting share of foundations, and charity of foundations. For BO, we can only evaluate RoA differences at the mean; for RO, we evaluate RoA differences at the mean, the median, the 25 percent quantile, and the 75 percent quantile.

The construction of our variables and the assumptions for identification require some adjustments in the estimation procedures. For models that look at a restricted sample, e.g., according to accounting standards, all firms that do not fulfill this requirement are removed.

To account for the impact of the financial crisis, all models contain a time dummy indicating if the RoA time series of a firm contains the financial crisis year 2008. For firms that enter the panel after 2008 this dummy has a value of zero. Except for model 1, industry fixed effects are included. In practice, the Frisch-Waugh-Lovell results on partitioned regression (Frisch and Waugh (1933), Lovell (1963)) are used to first regress all firm policy variables and RoA on the corresponding crisis and industry dummies. Then, we take the residuals from the models as the firm policy variables and the RoA for the decomposition models. This is equivalent to demeaning all variables within industry and crisis status. In economic terms, models 2 to 7 represent a decomposition of differences in deviations from the industry (crisis) specific average RoAs and relate them to deviations from the industry (crisis) specific firm policy averages. Again, this is equivalent to modeling constant industry and crisis fixed effects for both groups simultaneously[4].

Common support adjustment is always done after controlling for any type of fixed effects or restricting the subsample which explains the slightly varying sample sizes even in the less restricted models. For all models a minima-maxima comparison[5] is applied; for each firm policy variable, we observe a minimum and a maximum for FoFs and Nons. Firms are removed that are out of the support range. A firm is out of the support range if at least one of its policy variables is smaller than the less extreme minimum of FoFs and Nons for this variable or larger than the less extreme maximum of FoFs and Nons for this variable. In practice, that only drops Nons. In addition, the sample is trimmed more severely according to OR rank. There is a single FoF that is very small. The outlier can be seen in Figure 6.2, lower right hand corner, at the left side tail of the FoFs in the OR rank category around 0.35. We remove this firm which is an extreme outlier, relative to the other FoFs. Consequently, the minima-maxima comparison is used after removing this outlier. Common support adjustment is required since else the counterfactual distribution and the corresponding decomposition terms are not well defined. In economic terms, it ensures that the characteristics of FoFs and Nons do not diverge too much which is likely to be reasonable for a meaningful comparison.

Note that, since the return on assets is an average over time, the residual variance is expected to be larger for firms that only enter the panel for a short time. Hence, to

[4]Note that for the copula based decomposition we are using, the within industry demeaned variables may avoid computational problems arising from a high number of industry dummies in the copula estimation.

[5]See Dehejia and Wahba (1999) in the context of propensity score trimming.

Table 7.1: Mean RO2/BO2 and RO3/BO3

Variable	BO2	RO2	BO3	RO3
Total Δ^v_O	-1.4502^{**}	-1.4595^{***}	-1.5106^{**}	-1.5363^{***}
	(0.6307)	(0.5236)	(0.6315)	(0.5582)
Structure Δ^v_S	-0.8023	-0.6591	-0.7604	-0.6509
	(0.6789)	(0.6284)	(0.6760)	(0.5833)
Composition Δ^v_X	-0.6479^{***}	-0.8005^{***}	-0.7502^{***}	-0.8853^{***}
	(0.1575)	(0.2284)	(0.1693)	(0.2316)
Dependence Δ^v_D	-	-0.1902^{*}	-	-0.0841
		(0.1079)		(0.1093)
Marginal Δ^v_M	-	-0.6103^{***}	-	-0.8012^{***}
		(0.2052)		(0.1974)
σ_{RoA}	-0.2933^{**}	-0.2430	-0.2843^{**}	-0.2890^{**}
	(0.1283)	(0.1589)	(0.1276)	(0.1357)
Leverage	0.1166^{*}	0.1498^{***}	0.1233^{*}	0.0972
	(0.0615)	(0.0377)	(0.0651)	(0.0734)
PPM	0.0149	0.0474	0.0145	-0.0138
	(0.0198)	(0.0666)	(0.0196)	(0.0466)
OR rank	-0.4861^{***}	-0.4602^{***}	-0.5053^{***}	-0.5457^{***}
	(0.0842)	(0.0882)	(0.0861)	(0.1029)
OR growth	-	-	-0.0983^{*}	-0.1266^{*}
			(0.0565)	(0.0700)
FoFs	108	108	108	108
Nons	11562	11562	11151	11151

This table shows mean decomposition estimates for BO and RO for models 2 and 3. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

get a more efficient estimate, all observations are weighted by the number of years that are used to construct the average RoA. The same weighting scheme is applied for the copula decomposition as well. However, this generates slight deviations in the overall differences between BO and RO that can be seen in the subsequent section. We regard these differences as negligible since they are usually in the second digit after the decimal point.

7.2. Decomposition Results of the Mean Difference

In addition to separately analyzing firm policy variables that seem to be relevant for RoA differences, we analyze their impact on RoA differences when conditioning on the other variables. All statements in the subsequent sections are valid conditional on all other differences being held fixed. For the baseline specification (model 2 and 3), the firm policy variables that we investigate are σ_{RoA}, leverage, PPM, OR rank, and, in addition, OR growth for model 3. In both models, we take industry fixed effects into account as described before. Here, we look at the RoA mean difference, i.e., we decompose the difference of the mean RoA of FoFs and that of Nons into its components. Table 7.1 shows the findings for BO and RO for the models 2 and 3. BO is a benchmark for RO since it can be considered a special case of RO under linear structural functions and a zero dependence effect. Here, Nons are the reference group: e.g., a coefficient of -1.45 as total effect for BO2 corresponds to an underperformance of FoFs by 1.45 percentage points. Note that when interpreting the estimation results for BO and RO, they must always be related to the difference in the performance. Hence, e.g., a negative estimate for the marginal effect of σ_{RoA} implies that the different level of risk that FoFs take, relative to Nons, makes them perform worse in comparison.

First, we analyze BO2 and RO2. The total difference, according to BO2, is 1.45 percentage points; it is significant at the 5 percent level. This difference is the sum of differences in firm policies (composition effect) which accounts for 0.65 percentage points (highly significant), and of structural or unexplained differences (structure effect) of FoFs and Nons: 0.80 percentage points (insignificant). For RO2, the total difference is 1.46 percentage points which is highly significant. The highly significant composition effect accounts for 0.80 percentage points. The structure effect is insignificant. Dependence effect and marginal effects of firm policy variables sum up to the composition effect. The dependence effect reflects different dependence structures of the explanatory variables for FoFs and Nons. It is slightly significant. More important is the highly significant sum of the marginal effects of firm policies, the total marginal effect, which accounts for 0.61 percentage points.

Regardless of analyzing BO2 or RO2, PPM turns out to not significantly contribute to the difference in mean RoAs. According to BO2, the difference in σ_{RoA} lowers the mean RoA of FoFs by 0.29 percentage points. For RO2, the magnitude of this effect is similar but, surprisingly, insignificant. According to theory, which predicts a positive relationship between risk and return, we would expect a significantly negative effect due to consistently lower σ_{RoA} in FoFs. The effect of leverage is positive for BO2 (slightly significant) and for RO2 (highly significant). This might reflect that lower levels of leverage, which are typical for FoFs, might be beneficial regarding RoA, relative to higher levels of leverage for

Nons. Size as measured by OR rank has a significantly negative effect of similar magnitude according to BO2 and RO2. FoFs are significantly larger. Potentially, large firms are subject to different constraints making them react slowlier to new market developments than small firms and, therefore, they generate relatively lower returns.

OR growth is added to the analysis in BO3 and RO3. Relative to model 2, the total effect rises by a negligible extent. The composition effect grows, whereas the structure effect remains insignificant. Thus, a larger proportion of the difference in mean RoAs can be explained by differences in firm policies. For RO3, the dependence effect is insignificant, in contrast to RO2, and the sum of marginal effects of firm policy variables is larger, relative to RO2.

We, now, turn to the impact of single firm policy variables on the total mean RoA difference for FoFs and Nons. PPM, again, turns out to be insignificant. In contrast to model 2, the effect of σ_{RoA} is significant, also for the Rothe decomposition. Here, it is negative which is in line with the well-documented positive relationship between risk and return due to lower σ_{RoA} in FoFs. The impact of leverage is not clear-cut: it is positive but only significant for BO3. As in model 2, the effect of OR rank is significantly negative. There seem to be many small Nons generating high returns even after trimming and conditioning on other firm policy variables. The impact of OR growth is slightly significantly negative for BO3 and RO3 reflecting lower financial performance due to lower growth rates in FoFs.

In general, differences at the mean between BO and RO are either a result of the dependence effect or, which is more likely here, a result of nonlinearities in the data generating process or misspecification of some models. For instance, under a correct RO specification, BO potentially overestimates the effect of leverage since our specification for BO cannot capture non-linearities. Except for RO3, the contribution of leverage at the mean seems to be positive. This suggests that the contribution of lower leverage in FoFs is beneficial for them with respect to the RoA difference. A potential mechanism here could be that Nons operate at relatively high levels of leverage, thus, restricting the funding of profitable investment opportunities. The impact of σ_{RoA} is significantly negative, except for RO2, where it is insignificant. This indicates that higher risk in Nons might lead to higher

Table 7.2: RO2: All Estimates, FoFs = 108, Nons = 11562

Variable	Q25	Median	Mean	Q75
Total Δ_O^v	0.4807	-0.2341	-1.4595^{***}	-2.2495^{***}
	(0.7836)	(0.6420)	(0.5236)	(0.5893)
Structure Δ_S^v	0.9594	0.3336	-0.6591	-1.0435
	(0.7976)	(0.6578)	(0.6284)	(0.6760)
Composition Δ_X^v	-0.4786^{***}	-0.5678^{***}	-0.8005^{***}	-1.2060^{***}
	(0.1720)	(0.1418)	(0.2284)	(0.2723)
Dependence Δ_D^v	-0.2688^{**}	-0.1227^{*}	-0.1902^{*}	-0.1347^{*}
	(0.1167)	(0.0684)	(0.1079)	(0.0788)
Marginal Δ_M^v	-0.2098^{*}	-0.4451^{***}	-0.6103^{***}	-1.0713^{***}
	(0.1221)	(0.1188)	(0.2052)	(0.2708)
σ_{RoA}	0.1863^{***}	-0.1558	-0.2430	-0.6348^{**}
	(0.0382)	(0.1010)	(0.1589)	(0.2894)
Leverage	0.1737^{***}	0.1219^{***}	0.1498^{***}	0.1003
	(0.0337)	(0.0337)	(0.0377)	(0.0646)
PPM	0.1416^{***}	0.0824^{*}	0.0474	-0.0332
	(0.0410)	(0.0470)	(0.0666)	(0.1051)
OR rank	-0.2441^{**}	-0.3344^{***}	-0.4602^{***}	-0.6621^{***}
	(0.0962)	(0.0774)	(0.0882)	(0.1353)

This table shows decomposition estimates for RO2. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

returns, in line with theory. In addition, the largest proportion of the total difference can be explained by different size of the firms. It turns out that even after conditioning on other firm policies, FoF size is detrimental to financial performance. This is potentially connected to slower adjustment processes of large firms. In addition, lower OR growth in FoFs contributes to lower mean RoA of FoFs.

One can conclude from these findings that differences in firm policy variables capture a significant proportion of return differences at the mean. Although some findings do not seem to be consistent (findings for leverage and for σ_{RoA}), we argue that, as explained before, estimated effects can be seen as lower bounds for true effects. Relying on this, the picture gets more clear-cut: lower levels of σ_{RoA}, higher levels of OR rank, and lower OR growth contribute to the mean RoA underperformance of FoFs, whereas lower levels of leverage offset this result. PPM differences do not seem to have an impact on mean RoA differences.

Table 7.3: RO3: All Estimates, FoFs = 108, Nons = 11151

Variable	Q25	Median	Mean	Q75
Total Δ_O^v	0.4235	−0.2910	−1.5363***	−2.3083***
	(0.8581)	(0.5648)	(0.5582)	(0.6391)
Structure Δ_S^v	0.8703	0.3667	−0.6509	−0.9990
	(0.8370)	(0.5756)	(0.5833)	(0.6504)
Composition Δ_X^v	−0.4468***	−0.6578***	−0.8853***	−1.3092***
	(0.1602)	(0.1547)	(0.2316)	(0.2722)
Dependence Δ_D^v	−0.0773	−0.0687	−0.0841	−0.0604
	(0.0945)	(0.0622)	(0.1093)	(0.0846)
Marginal Δ_M^v	−0.3695***	−0.5891***	−0.8012***	−1.2488***
	(0.1330)	(0.1386)	(0.1974)	(0.2561)
σ_{RoA}	0.1699***	−0.1784*	−0.2890**	−0.6525**
	(0.0334)	(0.1023)	(0.1357)	(0.2586)
Leverage	0.1574***	0.0888**	0.0972	0.0551
	(0.0370)	(0.0441)	(0.0734)	(0.1049)
PPM	0.1189***	0.0453	−0.0138	−0.0848
	(0.0383)	(0.0372)	(0.0466)	(0.0684)
OR rank	−0.2940***	−0.3660***	−0.5457***	−0.7669***
	(0.1056)	(0.0858)	(0.1029)	(0.1427)
OR growth	0.0646	−0.0416	−0.1266*	−0.2569***
	(0.0530)	(0.0567)	(0.0700)	(0.0823)

This table shows decomposition estimates for RO3. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

7.3. Decomposition Results of Quantile Differences

In addition to analyzing the differences in mean RoAs, the copula approach allows to conduct a detailed analysis at different quantiles. Thus, we can decompose RoA differences at different quantiles of the distributions to address potential heterogeneity. Table 7.2 shows the estimation results for model 2; Table 7.3 displays the findings for model 3 of the copula based decomposition[6]. For different quantiles, the RoA difference (”total effect”) varies. The difference seems to be the more pronounced the higher the quantile is. At the 25 percent quantile, the difference is even positive (indicating overperformance of FoFs) but insignificant. The difference in median RoAs is negative but insignificant. For the mean and the 75 percent quantile, the difference is significantly negative. These findings hold true for RO2 and RO3. Apparently, there seem to be some high-performing Nons driving the RoA difference at high quantiles. On the other hand, the return difference gets insignificant at low quantiles.

[6] The results for the means are already discussed in section 7.2 but they are included for the sake of comparability.

The composition effect seems to increase monotonically in absolute terms along the quantiles. It is always highly significant. This is confirmed by RO2 and RO3. While the dependence effect is slightly significant and negative at all quantiles for RO2, its significance vanishes when considering RO3 where OR growth is included as additional firm policy variable. The total marginal effect seems to be more relevant: except for the 25 percent quantile when regarding RO2 where it is slightly significant, it is highly significant for all the other quantiles, irrespective of RO2 or RO3. In absolute terms, it increases monotonically along the quantiles.

When analyzing the marginal effects of the firm policy variables, we find that the effect of differences in σ_{RoA} is decreasing monotonically along the quantiles: at the 25 percent quantile it is significantly positive for RO2 and RO3, at the median it is negative and slightly significant for RO3 and insignificant for RO2, at the 75 percent quantile it is significantly negative for RO2 and RO3. This might indicate that, even conditional on other policy variables, FoFs follow more stable firm policies, i.e., they are not willing to take a lot of risk. On the one hand, this might restrict high levels of RoA (see underperformance of FoFs at the 75 percent quantile). On the other hand, this also might avoid very low RoA levels (see (insignificant) overperformance of FoFs at the 25 percent quantile). Concerning the leverage, we find that its effect decreases along the quantiles: leverage has the strongest positive and most significant impact at the 25 percent quantile for RO2 and RO3, at the median it is still positve and highly significant for RO2 and significant for RO3, at the 75 percent quantile significance vanishes. This suggests that typically lower levels of leverage offset the effect of other firm policy variables that are disadvantageous for FoFs in terms of financial performance for lower quantiles but do not matter for higher quantiles. Apparently, at lower quantiles, firms with a lower leverage (FoFs) have more scope to invest into profitable investments, whereas highly indebted firms are restricted to do so. For high-performing firms a high leverage might not represent a source of investment restriction. The impact of PPM is highly significant at the 25 percent quantile for RO2 and RO3, it is slightly significant at the median for RO2. Whenever it is significant, its sign is positive. Thus, for low quantiles, stronger substitution of raw material by labor seems to contribute to better financial performance of FoFs. For size, as measured by OR rank, the findings are clear-cut: its effect is highly significant (except for the 25 percent quantile when analyzing RO2, where it is only significant at the 5 percent level) and increases monotonically in absolute terms along the quantiles. The bigger size of FoFs, as measured by OR rank, seems to be a disadvantage for FoFs in terms of financial performance. There seem to be small or medium size Nons generating high returns and, thus, driving the RoA difference. This is consistent with the finding of Banz (1981) who documents that small firms have higher risk-adjusted stock returns than larger firms. OR growth is only included in RO3. Its effect is insignificant, except for the 75 percent RoA difference where it is highly significant and negative. Different growth rates of FoFs and Nons - on average, they are higher for Nons - might drive the RoA difference for high-performing FoFs and Nons.

Overall, the RoA difference for high-performing FoFs and Nons (75 percent quantile) is driven by differences in σ_{RoA}, OR rank, and OR growth. Apparently, there are several Nons that take more risk, are smaller and, thus, more dynamic, and grow faster than FoFs which results in the large RoA discrepancy. For average performers (median), there is an underperformance of FoFs which is insignificant. Still, size differences, as measured by OR rank, have a negative impact on FoF performance. This effect is partly offset by different levels of leverage in FoFs. It is likely that generally lower levels of leverage in FoFs lead to more freedom regarding investment opportunities, in contrast to being restricted by too much debt which might be the case for Nons. For low-performing FoFs and Nons, there is even underperformance of Nons, but this effect is insignificant. Only differences in OR rank drive underperformance of FoFs. This effect is overcompensated by differences in σ_{RoA}, leverage, and PPM. Apparently, there are low-performing Nons having taken too much risk, as well as being exposed to a high leverage restricting further investment opportunities. The significant effect of PPM is not easy to interpret. It may be that more outsourcing, as indicated by lower levels of PPM in Nons, is not beneficial regarding RoA.

7.4. Robustness Checks

7.4.1. Setup

We perform the analysis for five additional specifications to assure robustness of the major findings in the previous subsection. In addition to estimating model 2 and 3, we estimate model 1 which is the same as model 2 without accounting for industry fixed effects. Model 4, 5, 6, and 7 are the same as model 3 but, additionally, exclude listed firms (model 4), only include firms using German accounting standards ("HGB") (model 5), HGB firms and FoFs whose owning foundations have a voting share of at least 25 percent (model 6), and HGB firms and FoFs whose owning foundations are charitable (model 7). Check marks in the corresponding tables display the specifications of the models. The discussion focuses on major differences, relative to model 2 and 3.

7.4.2. Mean Differences

We display the findings for the difference in mean RoAs in Table 7.4 for BO and in Table 7.5 for RO. Only for model 1, the structure effect is significant (BO) or slightly significant (RO). This is no surprise since model 1 does not take industry effects into account not capturing structural differences among certain industries.

Models 4, 5, and 6 do not display significant effects of σ_{RoA}, leverage, and OR growth. This might be a consequence of the sample restrictions leading to only few FoFs. Anyway, for RO2 and RO3, the effects of σ_{RoA} and leverage are also not always significant as seen before. But as described before, one has to be aware of the fact that the estimates displayed have to be understood as lower bounds for the true effects. Due to this, one does not need to conclude that the results are inconsistent. Based on this reasoning, we, rather, want to point to the findings of model 2 and 3 which seem to be the most appropriate models in our setup, at least with respect to the number of observations. Having this in mind, their findings do not seem to be contradicted by the other models. Anyway, the estimates of OR rank are consistent, and OR rank turns out to be the most important driver of mean RoA differences.

Table 7.4: Blinder Oaxaca Decomposition

Variable	BO1	BO2	BO3	BO4	BO5	BO6	BO7
Total Δ_O^v	$-1.9502^{\star\star\star}$	$-1.4502^{\star\star}$	$-1.5106^{\star\star}$	$-1.7708^{\star\star\star}$	$-1.6561^{\star\star}$	$-1.3043^{\star}$	$-1.5063^{\star}$
	(0.5727)	(0.6307)	(0.6315)	(0.6568)	(0.7431)	(0.7767)	(0.7935)
Structure Δ_S^v	$-1.2276^{\star\star}$	-0.8023	-0.7604	-1.1004	-0.9968	-0.7195	-1.0864
	(0.6204)	(0.6789)	(0.6760)	(0.7050)	(0.7904)	(0.8259)	(0.8389)
Composition Δ_X^v	$-0.7226^{\star\star\star}$	$-0.6479^{\star\star\star}$	$-0.7502^{\star\star\star}$	$-0.6704^{\star\star\star}$	$-0.6593^{\star\star\star}$	$-0.5847^{\star\star\star}$	$-0.4199^{\star}$
	(0.1554)	(0.1575)	(0.1693)	(0.1790)	(0.1930)	(0.2088)	(0.2260)
σ_{RoA}	$-0.3239^{\star\star\star}$	$-0.2933^{\star\star}$	$-0.2843^{\star\star}$	-0.2183	-0.1764	-0.1871	-0.1832
	(0.1201)	(0.1283)	(0.1276)	(0.1340)	(0.1456)	(0.1633)	(0.1781)
Leverage	$0.1096^{\star\star}$	$0.1166^{\star}$	$0.1233^{\star}$	0.1042	0.1166	0.1322	$0.1918^{\star\star}$
	(0.0465)	(0.0615)	(0.0651)	(0.0718)	(0.0796)	(0.0871)	(0.0927)
PPM	-0.0165	0.0149	0.0145	0.0234	0.0123	0.0176	0.0332
	(0.0217)	(0.0198)	(0.0196)	(0.0264)	(0.0207)	(0.0254)	(0.0382)
OR rank	$-0.4918^{\star\star\star}$	$-0.4861^{\star\star\star}$	$-0.5053^{\star\star\star}$	$-0.4888^{\star\star\star}$	$-0.5170^{\star\star\star}$	$-0.4894^{\star\star\star}$	$-0.4236^{\star\star\star}$
	(0.0867)	(0.0842)	(0.0861)	(0.0868)	(0.0906)	(0.0902)	(0.0909)
OR growth	-	-	$-0.0983^{\star}$	-0.0909	-0.0948	-0.0581	-0.0382
			(0.0565)	(0.0614)	(0.0716)	(0.0718)	(0.0947)
Industry	-	✓	✓	✓	✓	✓	✓
HGB	-	-	-	-	✓	✓	✓
No Listed	-	-	-	✓	-	-	-
Voting Share > 25%	-	-	-	-	-	✓	-
Charitable only	-	-	-	-	-	-	✓
FoFs	108	108	108	100	87	77	65
Nons	11406	11562	11151	10916	10170	10711	9935

This table shows decomposition estimates for BO for all the models. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

Table 7.5: Copula Decomposition: Mean

Variable	RO1	RO2	RO3	RO4	RO5	RO6	RO7
Total Δ_O^v	-1.9698^{***}	-1.4595^{***}	-1.5363^{***}	-1.7539^{***}	-1.6522^{**}	-1.2342^{*}	-1.4098^{*}
	(0.5536)	(0.5236)	(0.5582)	(0.6008)	(0.6943)	(0.7002)	(0.8536)
Structure Δ_S^v	-1.1354^{*}	-0.6591	-0.6509	-1.0369	-0.9510	-0.4919	-0.7643
	(0.6182)	(0.6284)	(0.5833)	(0.6466)	(0.7351)	(0.7445)	(0.8492)
Composition Δ_X^v	-0.8344^{***}	-0.8005^{***}	-0.8853^{***}	-0.7170^{***}	-0.7012^{***}	-0.7423^{**}	-0.6454^{*}
	(0.2040)	(0.2284)	(0.2316)	(0.2068)	(0.2412)	(0.3203)	(0.3299)
Dependence Δ_D^v	-0.1816	-0.1902^{*}	-0.0841	-0.0208	0.0014	-0.1057	-0.2074^{*}
	(0.1134)	(0.1079)	(0.1093)	(0.0953)	(0.0975)	(0.1081)	(0.1150)
Marginal Δ_M^v	-0.6528^{***}	-0.6103^{***}	-0.8012^{***}	-0.6962^{***}	-0.7027^{***}	-0.6366^{**}	-0.4380
	(0.1946)	(0.2052)	(0.1974)	(0.1893)	(0.2300)	(0.3053)	(0.3099)
σ_{RoA}	-0.2806^{*}	-0.2430	-0.2890^{**}	-0.1984	-0.1871	-0.1872	-0.1398
	(0.1454)	(0.1589)	(0.1357)	(0.1253)	(0.1704)	(0.1952)	(0.1987)
Leverage	0.1716^{***}	0.1498^{***}	0.0972	0.1115	0.0919	0.1102	0.2362^{**}
	(0.0589)	(0.0377)	(0.0734)	(0.0866)	(0.0806)	(0.1021)	(0.1115)
PPM	0.0751	0.0474	-0.0138	0.0347	-0.0113	-0.0043	0.0637
	(0.0718)	(0.0666)	(0.0466)	(0.0496)	(0.0391)	(0.0476)	(0.0664)
OR rank	-0.4182^{***}	-0.4602^{***}	-0.5457^{***}	-0.4934^{***}	-0.5372^{***}	-0.5212^{***}	-0.4073^{***}
	(0.1095)	(0.0882)	(0.1029)	(0.1089)	(0.0964)	(0.0969)	(0.1014)
OR growth	-	-	-0.1266^{*}	-0.0868	-0.1203	-0.0835	-0.0120
			(0.0700)	(0.0661)	(0.0815)	(0.0869)	(0.1103)
Industry	-	✓	✓	✓	✓	✓	✓
HGB	-	-	-	-	✓	✓	✓
No Listed	-	-	-	✓	-	-	-
Voting Share > 25%	-	-	-	-	-	✓	-
Charitable only	-	-	-	-	-	-	✓
FoFs	108	108	108	100	87	77	65
Nons	11406	11562	11151	10916	10170	10711	9935

This table shows mean decomposition estimates for RO for all the models. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

Table 7.6: Copula Decomposition: Q25

Variable	RO1	RO2	RO3	RO4	RO5	RO6	RO7
Total Δ_O^v	0.3958	0.4807	0.4235	0.1230	−0.7355	0.2302	0.2368
	(0.7127)	(0.7836)	(0.8581)	(0.9324)	(1.1684)	(1.0837)	(1.0410)
Structure Δ_S^v	0.7606	0.9594	0.8703	0.5186	−0.4097	0.6529	0.7302
	(0.7101)	(0.7976)	(0.8370)	(0.9103)	(1.1520)	(1.0785)	(0.9803)
Composition Δ_X^v	−0.3648***	−0.4786***	−0.4468***	−0.3956**	−0.3258**	−0.4227**	−0.4933**
	(0.1111)	(0.1720)	(0.1602)	(0.1753)	(0.1629)	(0.1988)	(0.2172)
Dependence Δ_D^v	−0.1306**	−0.2688**	−0.0773	−0.0380	−0.0009	−0.0845	−0.1958**
	(0.0648)	(0.1167)	(0.0945)	(0.0983)	(0.0908)	(0.0987)	(0.0946)
Marginal Δ_M^v	−0.2342***	−0.2098*	−0.3695***	−0.3576**	−0.3249***	−0.3382**	−0.2975
	(0.0888)	(0.1221)	(0.1330)	(0.1420)	(0.1261)	(0.1691)	(0.1824)
σ_{RoA}	0.1876***	0.1863***	0.1699***	0.1863***	0.1531***	0.1634***	0.1560***
	(0.0480)	(0.0382)	(0.0334)	(0.0328)	(0.0303)	(0.0326)	(0.0347)
Leverage	0.0716	0.1737***	0.1574***	0.1811***	0.1508***	0.1682***	0.1739***
	(0.0536)	(0.0337)	(0.0370)	(0.0343)	(0.0404)	(0.0393)	(0.0457)
PPM	0.2085***	0.1416***	0.1189***	0.1428***	0.1227***	0.1333***	0.1618***
	(0.0655)	(0.0410)	(0.0383)	(0.0404)	(0.0342)	(0.0343)	(0.0378)
OR rank	−0.1853**	−0.2441**	−0.2940***	−0.2611***	−0.2334**	−0.2554**	−0.2048**
	(0.0749)	(0.0962)	(0.1056)	(0.0992)	(0.0925)	(0.1044)	(0.0953)
OR growth	-	-	0.0646	0.0902*	0.0684	0.1021	0.1348
			(0.0530)	(0.0523)	(0.0569)	(0.0628)	(0.0824)
Industry	-	✓	✓	✓	✓	✓	✓
HGB	-	-	-	-	✓	✓	✓
No Listed	-	-	-	✓	-	-	-
Voting Share > 25%	-	-	-	-	-	✓	-
Charitable only	-	-	-	-	-	-	✓
FoFs	108	108	108	100	87	77	65
Nons	11406	11562	11151	10916	10170	10711	9935

This table shows 25 percent quantile decomposition estimates for RO for all the models. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

Table 7.7: Copula Decomposition: Median

Variable	RO1	RO2	RO3	RO4	RO5	RO6	RO7
Total Δ_O^v	-0.6286	-0.2341	-0.2910	-0.5530	-0.4691	0.2934	-0.5351
	(0.5481)	(0.6420)	(0.5648)	(0.5869)	(0.8538)	(0.9394)	(1.1241)
Structure Δ_S^v	0.1565	0.3336	0.3667	0.0093	0.0552	0.8509	-0.0412
	(0.5781)	(0.6578)	(0.5756)	(0.5923)	(0.8842)	(0.9535)	(1.1153)
Composition Δ_X^v	-0.7851^{***}	-0.5678^{***}	-0.6578^{***}	-0.5623^{***}	-0.5243^{***}	-0.5576^{***}	-0.4940^{*}
	(0.1561)	(0.1418)	(0.1547)	(0.1448)	(0.1618)	(0.2168)	(0.2598)
Dependence Δ_D^v	-0.1642^{**}	-0.1227^{*}	-0.0687	-0.0510	0.0040	-0.0566	-0.1124
	(0.0736)	(0.0684)	(0.0622)	(0.0569)	(0.0640)	(0.0668)	(0.0702)
Marginal Δ_M^v	-0.6209^{***}	-0.4451^{***}	-0.5891^{***}	-0.5112^{***}	-0.5283^{***}	-0.5009^{**}	-0.3815
	(0.1366)	(0.1188)	(0.1386)	(0.1396)	(0.1570)	(0.1999)	(0.2460)
σ_{RoA}	-0.2735^{***}	-0.1558	-0.1784^{*}	-0.1132	-0.1193	-0.1306	-0.1053
	(0.1035)	(0.1010)	(0.1023)	(0.0955)	(0.1274)	(0.1362)	(0.1564)
Leverage	0.0877^{**}	0.1219^{***}	0.0888^{**}	0.1057^{**}	0.0689	0.0889	0.1871^{**}
	(0.0401)	(0.0337)	(0.0441)	(0.0530)	(0.0531)	(0.0648)	(0.0870)
PPM	0.0372	0.0824^{*}	0.0453	0.0904^{*}	0.0524	0.0735	0.1406^{**}
	(0.0456)	(0.0470)	(0.0372)	(0.0484)	(0.0443)	(0.0522)	(0.0700)
OR rank	-0.3585^{***}	-0.3344^{***}	-0.3660^{***}	-0.3452^{***}	-0.3900^{***}	-0.3766^{***}	-0.3213^{***}
	(0.0885)	(0.0774)	(0.0858)	(0.0961)	(0.0787)	(0.0775)	(0.0878)
OR growth	-	-	-0.0416	-0.0194	-0.0523	-0.0200	0.0258
			(0.0567)	(0.0503)	(0.0665)	(0.0683)	(0.0918)
Industry	-	✓	✓	✓	✓	✓	✓
HGB	-	-	-	-	✓	✓	✓
No Listed	-	-	-	✓	-	-	-
Voting Share > 25%	-	-	-	-	-	✓	-
Charitable only	-	-	-	-	-	-	✓
FoFs	108	108	108	100	87	77	65
Nons	11406	11562	11151	10916	10170	10711	9935

This table shows median decomposition estimates for RO for all the models. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

Table 7.8: Copula Decomposition: Q75

Variable	RO1	RO2	RO3	RO4	RO5	RO6	RO7
Total Δ^v_O	-3.4793^{***}	-2.2495^{***}	-2.3083^{***}	-2.2090^{***}	-2.1036^{**}	-1.9096^{*}	-2.0156
	(0.5083)	(0.5893)	(0.6391)	(0.7180)	(0.8514)	(0.9784)	(1.2639)
Structure Δ^v_S	-2.1452^{***}	-1.0435	-0.9990	-1.1771	-1.0633	-0.8704	-1.2152
	(0.6134)	(0.6760)	(0.6504)	(0.7502)	(0.9086)	(0.9876)	(1.3250)
Composition Δ^v_X	-1.3341^{***}	-1.2060^{***}	-1.3092^{***}	-1.0319^{***}	-1.0403^{***}	-1.0392^{**}	-0.8004
	(0.2575)	(0.2723)	(0.2722)	(0.2620)	(0.3385)	(0.4491)	(0.4902)
Dependence Δ^v_D	-0.1046	-0.1347^{*}	-0.0604	0.0155	0.0046	-0.1047	-0.2218^{*}
	(0.0685)	(0.0788)	(0.0846)	(0.0880)	(0.0872)	(0.1094)	(0.1286)
Marginal Δ^v_M	-1.2295^{***}	-1.0713^{***}	-1.2488^{***}	-1.0474^{***}	-1.0449^{***}	-0.9345^{**}	-0.5786
	(0.2514)	(0.2708)	(0.2561)	(0.2607)	(0.3483)	(0.4537)	(0.4726)
σ_{RoA}	-0.7923^{***}	-0.6348^{**}	-0.6525^{**}	-0.4960^{**}	-0.4731	-0.4790	-0.3956
	(0.2453)	(0.2894)	(0.2586)	(0.2397)	(0.3236)	(0.3642)	(0.3523)
Leverage	0.1706^{***}	0.1003	0.0551	0.0718	0.0659	0.0859	0.2586^{*}
	(0.0532)	(0.0646)	(0.1049)	(0.1240)	(0.1221)	(0.1639)	(0.1486)
PPM	-0.0375	-0.0332	-0.0848	-0.0240	-0.0526	-0.0335	0.0825
	(0.0927)	(0.1051)	(0.0684)	(0.0909)	(0.0777)	(0.0983)	(0.1187)
OR rank	-0.7240^{***}	-0.6621^{***}	-0.7669^{***}	-0.6697^{***}	-0.8007^{***}	-0.7243^{***}	-0.5663^{***}
	(0.1321)	(0.1353)	(0.1427)	(0.1503)	(0.1394)	(0.1368)	(0.1362)
OR growth	-	-	-0.2569^{***}	-0.2156^{**}	-0.2582^{**}	-0.2116^{*}	-0.0975
			(0.0823)	(0.0881)	(0.1124)	(0.1120)	(0.1266)
Industry	-	✓	✓	✓	✓	✓	✓
HGB	-	-	-	-	✓	✓	✓
No Listed	-	-	-	✓	-	-	-
Voting Share > 25%	-	-	-	-	-	✓	-
Charitable only	-	-	-	-	-	-	✓
FoFs	108	108	108	100	87	77	65
Nons	11406	11562	11151	10916	10170	10711	9935

This table shows 75 percent quantile decomposition estimates for RO for all the models. Bootstrapped standard errors are in parentheses. *, ** and *** denote 10%, 5%, and 1% significance levels.

7.4.3. Quantile Differences

We display the findings for the difference in 25 percent quantile RoAs in Table 7.6, for the difference in median RoAs in Table 7.7, and for the difference in 75 percent quantile RoAs in Table 7.8.

Most of the findings for the 25 percent quantile appear to be consistent for all the models. Varying significance levels of the dependence effect are one exception. The total marginal effect is not significant for model 7, in contrast to the other models. The findings for σ_{RoA}, leverage, PPM, and OR rank seem to be consistent; only for model 1, leverage is insignificant. Model 4 is the only model where OR growth is at least slightly significant.

For median RoAs, the findings are not clear-cut. Only for model 1 and 2, the dependence effect is significant or slightly significant, respectively. Model 7 is the only model whose total marginal effect is insignificant, possibly due to the small number of FoFs taken into account. Only for model 1 and 3 the impact of σ_{RoA} is negative and (slightly) significant. Leverage turns out to be significantly positive, except for model 5 and 6. The picture for PPM is not clear-cut at all. Again, OR rank turns out to be highly significant and negative for all models. We remind of the fact that estimated effects are lower bounds (in absolute terms) for the true effects. Considering this and observing that the signs of the estimates are consistent, we conclude that the findings for the different models might support consistency.

The picture looks similar for the 75 percent quantile. For model 7, we do not find a significant total effect; the composition effect is insignificant, while the dependence effect is slightly significant. Besides, we see a highly significant structure effect for model 1, possibly due to not taking industry fixed effects into account moving the additional heterogeneity to the unexplained or structural component. σ_{RoA} is insignificant for model 5, 6, and 7. Leverage turns out to be positive and highly significant for model 1 and slightly significant for model 7. The effect for PPM is insignificant for all models, while the effect of OR rank is significantly negative for all models. Except for model 7, OR growth turns out significant and negative. Again, we refer to the fact that these estimates have to be interpreted as lower bounds of the true effects. Taking this into consideration and observing consistent signs of estimated firm policy effects across the models, we believe that these findings support the findings of baseline models 2 and 3.

8. Conclusion

In this paper, we study if and how differences in firm policies have an impact on differences in return on assets of FoFs and Nons. We perform the analysis for return differences at the mean and at several quantiles. We document that for high-performing FoFs and Nons the RoA difference is more pronounced in favor of Nons, for low-performing firms the difference vanishes. Performance differences are substantially driven by differences in firm policies. We find that (1) lower risk in FoFs, as measured by the standard deviation of return on assets, increases FoF underperformance at high quantiles, but offsets it at low quantiles, (2) a lower leverage of FoFs offsets FoF underperformance at low quantiles and the median, (3) higher labor intensity in FoFs offsets their underperformance at low quantiles, (4) the larger size of FoFs increases FoF underperformance for the mean and all quantiles, (5) lower growth rates of FoFs increase FoF underperformance at high quantiles, and (6) residual differences beyond firm policies tend to be insignificant.

Managers of FoFs might be less incentivized to take higher risk which is likely to be a driver of lower but more stable returns in FoFs, while there seem to be several Nons generating very high returns. A lower leverage in FoFs appears to give more scope to new investment opportunities and, thus, partly offsets the performance disadvantage of FoFs. More labor intensity in FoFs might be interacted with less outsourcing. Possibly, some Nons have overdone outsourcing reducing the performance gap. The larger size of FoFs involves less flexibility and lower adjustment to new market conditions resulting to higher RoA difference. Slower growth of FoFs might translate into lower returns.

By the construction of the variables we try to mitigate the simultaneity bias adherent in accounting information. We show that under this potential bias estimates have to be interpreted as lower bounds for true effects. The more persistent the variables are, the closer the estimates get to true effects.

This study might contribute to a better understanding about the impact of today's firm policies on future returns since it can be interpreted as a predictive approach due to the construction of the variables. As far as it is possible, a manager of a Non might adjust a certain variable towards the level which can be observed in FoFs for this variable and vice versa in order to push future returns into the desired direction. Further studies on the relationship between present firm policies and future returns combined with conversations with practitioners might deepen our understanding.

Appendix A Parameter Proofs

The models for the time averages are given by

$$\bar{Y}_i = \bar{X}_i\beta + \bar{Z}_i\gamma + \bar{\varepsilon}_i,$$
$$\bar{Z}_i = \bar{X}_i\alpha + \bar{Y}_i\delta + \bar{u}_i.$$

Let the model stacked over all observations be denoted as

$$Y = X\beta + Z\gamma + \varepsilon,$$
$$Z = X\alpha + Y\delta + u$$

with all elements being vectors of size n and all parameters being scalars. We assume that $E[\bar{X}_i\bar{\varepsilon}_i] = E[\bar{X}_i\bar{u}_i] = 0$ and without loss of generality that all variables have mean zero, i.e., are centered. For the sake of simplicity we assume that the errors are uncorrelated across equations. In addition, we assume the usual regularity conditions to assure that all empirical correlation and variance covariance matrices converge to a fixed matrix in probability. In the following, we derive the probability limits for the least squares estimation of β and γ. One can rewrite the outcomes as

$$\begin{aligned} Y &= X\beta + Z\gamma + \varepsilon \\ &= X\beta + (X\alpha + Y\delta + u)\gamma + \varepsilon \\ \Leftrightarrow Y &= X\left(\frac{\beta + \alpha\gamma}{1-\delta\gamma}\right) + u\left(\frac{\gamma}{1-\delta\gamma}\right) + \varepsilon\left(\frac{1}{1-\delta\gamma}\right) \\ \Rightarrow Z &= X\left(\frac{\alpha + \beta\delta}{1-\delta\gamma}\right) + u\left(\frac{1}{1-\delta\gamma}\right) + \varepsilon\left(\frac{\delta}{1-\delta\gamma}\right). \end{aligned}$$

Let for any n times k dimensional matrix W the residual maker matrix be defined as $M_W = I - W(W'W)^{-1}W'$, σ^2_L be the variance of a random variable L, $\sigma^2_{L,S}$ the covariance between two random variables L and S, and $\rho_{L,S}$ their correlation coefficient. The closed form solution for the least squares estimate of β is given by

$$
\begin{aligned}
\hat{\beta} &= (X'M_ZX)^{-1}X'M_ZY \\
&= (X'M_ZX)^{-1}X'M_ZX\Big(\frac{\beta+\alpha\gamma}{1-\delta\gamma}\Big) + (X'M_ZX)^{-1}X'M_Z\Big[u\Big(\frac{\gamma}{1-\delta\gamma}\Big)+\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big] \\
&= \Big(\frac{\beta+\alpha\gamma}{1-\delta\gamma}\Big) + (X'M_ZX)^{-1}\Big\{X'\Big[u\Big(\frac{\gamma}{1-\delta\gamma}\Big)+\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big] \\
&\quad - X'Z(Z'Z)^{-1}Z'\Big[u\Big(\frac{\gamma}{1-\delta\gamma}\Big)+\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big]\Big\} \\
&= \Big(\frac{\beta+\alpha\gamma}{1-\delta\gamma}\Big) + (X'X - X'Z(Z'Z)^{-1}Z'X)^{-1}\Big\{X'\Big[u\Big(\frac{\gamma}{1-\delta\gamma}\Big)+\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big] \\
&\quad - X'Z(Z'Z)^{-1}Z'\Big[u\Big(\frac{\gamma}{1-\delta\gamma}\Big)+\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big]\Big\}.
\end{aligned}
$$

As auxiliary result we use that

$$
\begin{aligned}
n^{-1}Z'u &= n^{-1}X'u\Big(\frac{\alpha+\beta\delta}{1-\delta\gamma}\Big) + n^{-1}u'u\Big(\frac{1}{1-\delta\gamma}\Big) + n^{-1}\varepsilon'u\Big(\frac{\delta}{1-\delta\gamma}\Big) \xrightarrow{p} \frac{\sigma_u^2}{1-\delta\gamma} \\
n^{-1}Z'\varepsilon &= n^{-1}X'\varepsilon\Big(\frac{\alpha+\beta\delta}{1-\delta\gamma}\Big) + n^{-1}u'\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big) + n^{-1}\varepsilon'\varepsilon\Big(\frac{\delta}{1-\delta\gamma}\Big) \xrightarrow{p} \frac{\delta\sigma_\varepsilon^2}{1-\delta\gamma}
\end{aligned}
$$

and hence by multiplying and dividing through with n it follows that

$$
\begin{aligned}
\hat{\beta} &\xrightarrow{p} \frac{\beta+\alpha\gamma}{1-\delta\gamma} + \Big(\sigma_X^2 - \frac{\sigma_{X,Z}^2}{\sigma_Z^2}\Big)^{-1}\frac{\sigma_{X,Z}}{\sigma_Z^2}\Big[\frac{\gamma\sigma_u^2+\delta\sigma_\varepsilon^2}{(1-\delta\gamma)^2}\Big] \\
&= \frac{\beta+\alpha\gamma}{1-\delta\gamma} + \Big[\frac{\rho_{X,Z}}{\sigma_X\sigma_Z}\Big]\frac{\gamma\sigma_u^2+\delta\sigma_\varepsilon^2}{(1-\rho_{X,Z}^2)(1-\delta\gamma)^2}.
\end{aligned}
$$

With the intermediary step from above one can show that the OLS estimate of γ yields

$$
\begin{aligned}
\hat{\gamma} &= (Z'M_XZ)^{-1}Z'M_XY \\
&= (Z'M_XZ)^{-1}Z'[Y - X(X'X)^{-1}X'Y] \\
&= (Z'M_XZ)^{-1}\Big\{\Big[Z'X\Big(\frac{\beta+\alpha\gamma}{1-\delta\gamma}\Big) + Z'u\Big(\frac{\gamma}{1-\delta\gamma}\Big) + Z'\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big] \\
&\quad - Z'X(X'X)^{-1}\Big[X'X\Big(\frac{\beta+\alpha\gamma}{1-\delta\gamma}\Big) + X'u\Big(\frac{\gamma}{1-\delta\gamma}\Big) + X'\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big]\Big\} \\
&= (Z'M_XZ)^{-1}\Big[Z'u\Big(\frac{\gamma}{1-\delta\gamma}\Big) + Z'\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big) \\
&\quad - Z'X(X'X)^{-1}\Big\{X'u\Big(\frac{\gamma}{1-\delta\gamma}\Big) + X'\varepsilon\Big(\frac{1}{1-\delta\gamma}\Big)\Big\}\Big].
\end{aligned}
$$

Using the identification and convergence assumptions and plugging in Z, we obtain

$$\begin{aligned}
\hat{\gamma} &= (Z'M_XZ)^{-1}\left[\frac{\gamma}{1-\delta\gamma}Z'u + \frac{1}{1-\delta\gamma}Z'\varepsilon\right] + o_p(1) \\
&= (Z'M_XZ)^{-1}\left[\frac{\gamma}{1-\delta\gamma}\left\{X'u\left(\frac{\alpha+\beta\gamma}{1-\delta\gamma}\right) + u'u\left(\frac{1}{1-\delta\gamma}\right) + \varepsilon'u\left(\frac{\delta}{1-\delta\gamma}\right)\right\}\right. \\
&\quad \left. + \frac{1}{1-\delta\gamma}\left\{X'\varepsilon\left(\frac{\alpha+\beta\gamma}{1-\delta\gamma}\right) + u'\varepsilon\left(\frac{1}{1-\delta\gamma}\right) + \varepsilon'\varepsilon\left(\frac{\delta}{1-\delta\gamma}\right)\right\}\right] + o_p(1) \\
&= (Z'M_XZ)^{-1}\left[\frac{\gamma}{(1-\delta\gamma)^2}u'u + \frac{\delta}{(1-\delta\gamma)^2}\varepsilon'\varepsilon\right] + o_p(1) \\
&= (Z'Z - Z'X(X'X)^{-1}X'Z)^{-1}\left[\frac{\gamma}{(1-\delta\gamma)^2}u'u + \frac{\delta}{(1-\delta\gamma)^2}\varepsilon'\varepsilon\right] + o_p(1)
\end{aligned}$$

and hence it follows that

$$\begin{aligned}
\hat{\gamma} &\xrightarrow{p} \left[\sigma_Z^2 - \frac{\sigma_{X,Z}^2}{\sigma_X^2}\right]^{-1}\frac{\gamma\sigma_u^2 + \delta\sigma_\varepsilon^2}{(1-\delta\gamma)^2} \\
&= \frac{\gamma\sigma_u^2 + \delta\sigma_\varepsilon^2}{(1-\rho_{X,Z}^2)\sigma_Z^2(1-\delta\gamma)^2}.
\end{aligned}$$

Now, consider the auxiliary model with lagged regressors Z_{i0} assuming that the prior values are not subject to simultaneity bias, i.e., $E[Z_{i0}\bar{\varepsilon}_i] = E[Z_{i0}\bar{u}_i] = 0$. Let Z_0 be the stacked vector of the predetermined regressors. To put persistence into a model, say that the dynamics of leverage are appropriately captured by a stationary AR(1) structure, i.e., we have that

$$Z_{it} = \theta Z_{it-1} + \nu_{it} \Leftrightarrow Z_{it} = Z_{i0}\theta^t + \sum_{j=0}^{t-1}\theta^j\nu_{it-j}$$

with ν_{it} being some independent zero mean error. This could be easily relaxed and merely serves illustrative purpose. Taking averages for the leverage over $t = 1, \ldots, T$ yields

$$\begin{aligned}
\bar{Z}_i &= Z_{i0}\frac{1}{T}\sum_{t=1}^{T}\theta^t + \frac{1}{T}\sum_{t=1}^{T}\sum_{j=0}^{t-1}\theta^j\nu_{it-j} \\
&\equiv Z_{i0}\Theta + N_i \\
\Leftrightarrow Z &= Z_0\Theta + N.
\end{aligned}$$

Therefore, the auxiliary model for estimation is given by

$$Y = X\beta + Z_0\omega + \nu$$

with $\nu = \varepsilon - Z_0\omega + Z\gamma$. Using the additional orthogonality condition as well as the independence of the error in the autoregressive model, one can derive the probability limits for the least squares estimator of the auxiliary model parameters

$$
\begin{aligned}
\hat{\beta} &= (X' M_{Z_0} X)^{-1} X' M_{Z_0} Y \\
&= (X' M_{Z_0} X)^{-1} X' M_{Z_0} (X\beta + Z\gamma + \varepsilon) \\
&= \beta + (X' M_{Z_0} X)^{-1} X' M_{Z_0} Z\gamma + (X' M_{Z_0} X)^{-1} X' M_{Z_0} \varepsilon \\
&= \beta + (X' M_{Z_0} X)^{-1} X' M_{Z_0} (Z_0\Theta + N)\gamma + (X' M_{Z_0} X)^{-1} X' M_{Z_0} \varepsilon \\
&= \beta + (X' M_{Z_0} X)^{-1} X' M_{Z_0} (N\gamma + \varepsilon) \\
&\xrightarrow{p} \beta.
\end{aligned}
$$

Hence, we can estimate β consistently. For the new parameter ω on the lagged regressor one obtains that

$$
\begin{aligned}
\hat{\omega} &= (Z_0' M_X Z_0)^{-1} Z_0 M_X Y \\
&= (Z_0' M_X Z_0)^{-1} Z_0 M_X (X\beta + Z\gamma + \varepsilon) \\
&= \Theta\gamma + (Z_0' M_X Z_0)^{-1} Z_0 M_X (N\gamma + \varepsilon) \\
&\xrightarrow{p} \Theta\gamma
\end{aligned}
$$

which under stationarity is an absolutely lower bound for the effect size γ from the true structural equation which completes the proof.

References

Altonji, J. G., Bharadwaj, P., and Lange, F. (2012). Changes in the Characteristics of American Youth: Implications for Adult Outcomes.

Banz, R. W. (1981). The Relationship between Return and Market Value of Common Stocks. *Journal of financial economics*, 9(1):3–18.

Bekaert, G. and Wu, G. (2000). Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, 13(1):1–42.

Bingham, J. B., Dyer Jr, W. G., Smith, I., and Adams, G. L. (2011). A Stakeholder Identity Orientation Approach to Corporate Social Performance in Family Firms. *Journal of business ethics*, 99(4):565–585.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *Journal of Human resources*, pages 436–455.

Chernozhukov, V., Fernández-Val, I., and Melly, B. (2013). Inference on counterfactual distributions. *Econometrica*, 81(6):2205–2268.

Chirico, F. and Bau, M. (2014). Is the Family an ”Asset” or ”Liability” for Firm Performance? The Moderating Role of Environmental Dynamism. *Journal of Small Business Management*, 52(2):210–225.

Dehejia, R. H. and Wahba, S. (1999). Causal Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*, 94(448):1053–1062.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1995). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64:1001–1044.

Draheim, M. and Franke, G. (2015). Foundation-owned Firms in Germany: Governance and Performance.

Duffee, G. R. (1995). Stock Returns and Volatility a Firm-level Analysis. *Journal of Financial Economics*, 37(3):399–420.

Evans, D. S. (1987). The Relationship between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries. *The journal of industrial economics*, pages 567–581.

Firpo, S., Fortin, N., and Lemieux, T. (2007). Unconditional Quantile Regressions. *Econometrica*, 77:259–276.

Firpo, S., Fortin, N. M., and Lemieux, T. (2013). Occupational Tasks and Changes in the Wage Structure.

Fleschutz, K. (2009). *Die Stiftung als Nachfolgeinstrument für Familienunternehmen*. Springer.

Foresi, S. and Peracchi, F. (1995). The Conditional Distribution of Excess Returns: An Empirical Analysis. *Journal of the American Statistical Association*, 90(430):451–466.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition Methods in Economics. *Handbook of labor economics*, 4:1–102.

Frisch, R. and Waugh, F. V. (1933). Partial Time Regressions as Compared with Individual Trends. *Econometrica: Journal of the Econometric Society*, pages 387–401.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The journal of finance*, 48(5):1779–1801.

Hanousek, J. and Shamshur, A. (2011). A Stubborn Persistence: Is the Stability of Leverage Ratios Determined by the Stability of the Economy? *Journal of Corporate Finance*, 17(5):1360–1376.

Herrmann, M. and Franke, G. (2002). Performance and Policy of Foundation-owned Firms in Germany. *European Financial Management*, 8(3):261–279.

Lemmon, M. L., Roberts, M. R., and Zender, J. F. (2008). Back to the Beginning: Persistence and the Cross-section of Corporate Capital Structure. *The Journal of Finance*, 63(4):1575–1608.

Lovell, M. C. (1963). Seasonal Adjustment of Economic Time Series and Mmultiple Regression Analysis. *Journal of the American Statistical Association*, 58(304):993–1010.

Machado, J. A. and Mata, J. (2005). Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression. *Journal of applied Econometrics*, 20(4):445–465.

Myers, S. C. (1977). Determinants of Corporate Borrowing. *Journal of financial economics*, 5(2):147–175.

Oaxaca, R. (1973). Male-female Wage Differentials in Urban Labor Markets. *International economic review*, pages 693–709.

Rothe, C. (2012). Partial Distributional Policy Effects. *Econometrica*, 80(5):2269–2301.

Rothe, C. (2015). Decomposing the Composition Effect. *Journal of Business & Economic Statistics*, 33:323–337.

Sklar, M. (1959). *Fonctions de répartition à n dimensions et leurs marges.* Université Paris 8.

Smith, C. W. (1977). Alternative Methods for Raising Capital: Rights versus Underwritten Offerings. *Journal of Financial Economics*, 5(3):273–307.

Strebulaev, I. A. and Yang, B. (2013). The Mystery of Zero-leverage Firms. *Journal of Financial Economics*, 109(1):1–23.

Thomsen, S. (1996). Foundation Ownership and Economic Performance1. *Corporate Governance: An International Review*, 4(4):212–221.

Thomsen, S. (1999). Corporate Ownership by Industrial Foundations. *European Journal of Law and Economics*, 7(2):117–137.

Thomsen, S. and Hansmann, H. (2013). The Performance of Foundation-owned Companies. *Available at SSRN 2406055.*

Thomsen, S. and Rose, C. (2004). Foundation Ownership and Financial Performance: Do Companies need Owners? *European Journal of Law and Economics*, 18(3):343–364.

Welch, I. (2004). Capital Structure and Stock Returns. *Journal of Political Economy*, 112(1):106–132.