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Executives' Short-Term and Long-Term Incentives - A Distributional Analysis

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Executives' Short-Term and Long-Term Incentives - A Distributional Analysis

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Abstract

Executives are often paid for short-term changes in shareholder wealth, but rational shareholders want executives to maximize long-term shareholder wealth. Incentives for short-term and long-term oriented behavior may depend on an executive's level of pay in the distribution, holding other factors constant. This paper tests for distributional heterogeneity of short-term and long-term incentives in a 12 year cross-country panel of executives. I use the band-pass filter to separate short-term and long-term shareholder wealth changes (Christiano and Fitzgerald, 2003), and estimate of the shareholder wealth-pay relation using method of moments-quantile regression, developed by Machado and Santos Silva (2019), which accounts for time-constant unobserved heterogeneity of executive-firm pairs across the distribution. When using yearly total compensation to measure pay, executives in the upper tail of the conditional compensation distribution have longer-term oriented incentives. In contrast, when accumulated executive wealth is used to measure pay, executives in the upper tail of the wealth distribution have shorter-term oriented incentives. Since executive wealth encompasses changes to executive utility after pay is granted through accumulated equity-linked pay, it is the preferred measure for evaluating equity-linked pay. Results thus suggest that equity-linked pay should have a longer vesting period for executives in the upper tail than in the lower tail. I find evidence that executives in the upper-tail are evaluated relatively to the industry's short-run and long-run performance.

Keywords: Executive Compensation, Method of Moments-Quantile Regression, Short-Term Performance, Long-Term Performance, Distribution, Benchmarking.
JEL Classification: J31, M12, M52.

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1 Introduction

There is an increasingly large empirical literature on executive and CEO compensation (see Edmans et al. 2017 for a recent survey). Median CEO pay for S&P 500 firms has increased sixfold since 1980 to US $10.1 million per year in 2014 (Edmans et al., 2017). Further, there have been volatile changes in pay inequality among executives.[1] Given nearly all research on incentives for executives examines the relation between an increase in firm performance and the executive's total pay, bonus or total wealth at the conditional mean. Thus an important and unanswered question is whether incentives for executives differ across the conditional distribution? This answer whether incentives of shareholders and executives are aligned differently across the conditional distribution, *not only on aggregate*, as the conditional mean analysis shows.

Further, research on wage distributions has largely been the focus of labor economists assessing factors influencing non-executive wages. While fruitful, it is equally as important to research the distributional differences in executive compensation, where there is a substantial amount of inequality, as well as many firm and government policies which have an effect on pay distributions. The structure of incentives, and legislation (e.g. say-on-pay acts in the UK and US) can potentially be used by researchers as exogenous variation (Ferri and Maber, 2013). This article serves as a starting point to show what can be done using relatively analogous methodology to existing literature on executive compensation, albeit in a distributional framework (Gibbons and Murphy, 1990; Jensen and Murphy, 1990).

I investigate whether sensitivity of executive pay to short and long-term firm and industry performance differs across the conditional distribution. I go a step further than

[1] The distribution of executive pay has significantly changed in past years, and will likely continue to evolve. Edmans et al. (2017) note that the difference between mean and median CEO compensation reduced from 67% in 2001 to 19% in 2014 for S&P 500 firms. As a result, thus choosing to represent "average" executive pay by the mean or the median will affect results. Both can be appropriate: Mean pay to assess aggregate levels in pay, median (and other quantiles) pay is relevant in assessing the pay for a typical CEO (Edmans et al., 2017; Murphy, 2013).

existing literature on this topic by using panel quantile regressions to account for time-constant unobserved heterogeneity (Machado and Santos Silva, 2019). This method makes results comparable to other panel estimates of performance pay-elasticities and relative performance evaluation (Gibbons and Murphy, 1990), identifying performance-pay sensitivities across the conditional distribution and using all data. I use total compensation and total wealth as measures for 'pay'. Total compensation is direct compensation and grant-date value of newly emitted stock-related pay. Total wealth is the estimated value of accumulated stock-related pay, options and long-term incentive plans (LTIP). Most executives have sizable equity stakes in their firm and stock-related pay, tying their wealth to market value of the firm (Edmans et al., 2017). I use cross-country panel data to generalize findings to outside the United States, which has been the focus of most research on executive compensation.

The main results show that no matter which measure of pay is used, incentives to maximise long-run firm performance are between three and seven times larger than short-term incentives at the conditional median. I find significant heterogeneity in incentives, showing that going 'beyond the mean' is important for research on executive compensation: Total compensation is more sensitive to short-term firm performance in the left tail of the conditional distribution, and more sensitive to long-term performance in the right tail of the conditional distribution. In contrast, total wealth is more sensitive to short-term firm performance in the right tail of the conditional distribution, and more sensitive to long-term performance in the left tail of the conditional distribution. A potential explanation for this finding is that wealth contains a much larger portion of equity-linked components, and is rarely ex-post adjusted after grant-date. The optimal vesting period for equity-linked compensation should potentially be longer for executives at the right tail of the conditional wealth distribution than those at the lower tail. Total compensation has a close to zero sensitivity to short-term industry performance, holding firm performance constant. I can not entirely rule out that firms engage in long-term industry benchmarking of executive compensation, as estimates are noisy. Coefficients of interest are not conditional on the fixed-effect of the manager in my approach, and thus interpretations are not conditional on a certain ability or unobserved factors. This is not necessarily the case for other quantile regression estimators accounting for unobserved heterogeneity. The results can be thought of as similar to a within-estimator (fixed effects regression) at a certain point in the conditional distribution. Although I do not claim that the results are causal, I can rule out that they are driven by time-constant factors such as ability, risk-tolerance, or persistent corporate governance regulations in a country or firm.

The paper proceeds as follows. Chapter 2 discusses related literature, and identifies hypotheses. Chapter 3 describes the data and empirical methodology used to generate main variables. Chapter 4 discusses the empirical methodology, especially the application of moments-quantile regression. Chapter 5 presents the main results and robustness checks, as well as potential starting points for future research. Chapter 6 discusses the interpretation of results and optimal executive compensation in light of the findings.

2 Related Literature and Hypothesis Development

This paper links to the literature on optimal contracting and the informativeness principle. According to the informativeness principle, in a principal-agent relationship (here shareholders and executives of a firm), risk-averse agents should ideally be rewarded positively for effort, net of observable exogenous factors affecting firm performance (Holmstrom, 1979). In my setting, the proxy for effort is firm's long-term market value, and industry average shareholder wealth and macroeconomic indicators are proxies for exogenous factors affecting firm performance. The long-term stock price captures all potential outcomes of CEO behavior (e.g., changes in growth or profit, restructuring) affecting shareholder value and is thus a valid proxy of firm performance (Jensen, 2001; Edmans et al., 2017). Gibbons and Murphy (1990) find evidence that firms do benchmark against the industry, but more strongly against the entire market than the industry. Other studies show mixed evidence of the informativeness principle, and that managers are rewarded positively for external forces affecting firm performance (Bertrand and Mullainathan, 2001).

A natural extension of the 'pay for luck' literature tests whether executives gain more from exogenous forces that positively affect firm performance measures than they lose if they negatively affect firm performance. This is known as asymmetric pay for luck, or asymmetric benchmarking in the literature (Garvey and Milbourn, 2006). Garvey and Milbourn (2006) estimate that for a CEO at the mean, the performance-pay relation is between 25% and 45% lower when the performance standard or benchmark is down than when it is up. Addressing a potential mechanism, Bizjak et al. (2008) find that asymmetric benchmarking serves as a tool to retain CEOs, and does not necessarily lead to poor corporate governance. In a comprehensive study testing robustness of this asymmetry, Daniel et al. (2019) find no significant interaction between bad luck and the pay benchmark in the majority of specifications for US firms, using over 200 regression specifications.

There are a number of limitations and unanswered questions to the above studies that require investigation. The first is to take a distributional approach assessing the strength of incentives for managers. To my knowledge, the only other study using a distributional framework to investigate differences in the strength of incentives across the conditional distribution of executives is by Hallock et al. (2010). They find significant differences in performance pay for conditionally predicted low earning and high earning CEOs, ranging from 0.0673 at the first decile, to 0.1456 at the 9th decile, using conditional quantile regressions (Koenker and Bassett Jr, 1978).

Second, most studies of the performance-pay relation do not differentiate between long and short-term firm performance. Firms optimally pay executives to maximize long-term firm performance (Jensen, 2001; Edmans et al., 2012, 2017). However, if stock or stock options vest during an executive's career, it can be rational for her to forgo positive-NPV projects which reduce short-term performance, engage in negative-NPV projects that boost short-term performance, pursue earnings management to boost short-term sales, and engage in accounting manipulation (Edmans et al., 2017). The optimal contract for a manager over a fixed time horizon, who can also engage in short-term behavior shifts vesting of a part of equity-related pay to retirement (Marinovic and Varas, 2019). This softens incentives to engage in short-term oriented behavior. The deferral of vesting equity is higher in the optimal contract, the stronger incentives are to engage in manipulation that increase short-term performance. However, lengthening the vesting period is costly for the executive, as it increases uncertainty through exposing the executive to risk outside her control (Edmans et al., 2017). Further, executives may reject risky, value-creating projects if they have a large amount of stock-related pay (Brisley, 2006). I observe the relation between pay and short-term, as well as long-term firm performance. I test whether incentives for short-term and long-term oriented behavior differ across the distribution. This is of relevance to firms, when deciding on the length of vesting periods of equity, and performance periods of other stock-related pay such as performance-based equity for executives with different (conditional) wealth or pay levels. This motivates the distributional framework in my regression analysis.

Third, I also test whether relative performance evaluation differs across the conditional distribution. In doing this, I differentiate between long and short-term industry performance. If compensation is negatively correlated with short-term industry performance, this can be understood to be because of risk-sharing between firms and CEOs (Gibbons and Murphy, 1990). Firms can adjust pay upwards in case economic conditions are bad, as the informativeness principle predicts will be done in an optimal contract. Further, if shareholders may benchmark the executive performance according to the firm's value *relative* to the industry's long-term performance, we may still see long-term relative performance evaluation. If the firm is in a declining industry, shareholders may still reward the manager more if the executive is performing well relative to the competitors. This motivates the investigation of pay sensitivity to long-term industry shareholder wealth, holding firm performance and other macroeconomic factors constant.

Based on the above arguments, I form hypotheses. I formalize the predictions for the equation representing the performance-pay relation at a quantile Q. The coefficients β represent the performance-pay sensitivity. The τ'th conditional quantile of the pay distribution is defined as $Q_Y(\tau|\cdot)$, and $Trend_{f,(s)}$ represents long-term performance of a firm f or industry s, and $Shock_{f,(s)}$ represents short-term firm or industry performance. The performance-pay relation at a given quantile can be written as

$$Q_Y(\tau|X) = \beta_1 Shock_f + \beta_2 Trend_f + \beta_3 Shock_s + \beta_4 Trend_s. \tag{1}$$

The equation shows a \$-\$ performance pay relation, as estimated by Jensen and Murphy (1990), but for a conditional quantile in the pay distribution. Taking the logarithm of each variable in equation (1), the coefficients are the performance-pay elasticity, or %-% relation between pay and performance. This elasticity is estimated below. This specification has a better theoretical foundation when estimating the size of incentives (Edmans et al., 2017).[2] Actions that contribute to firm value taken by the executive can have an effect that is proportional to firm size. For example, a corporate restructure will likely increase the %-performance of the firm (Edmans and Gabaix, 2016). On the other hand, perks, like buying a private jet, may only reduce \$-performance (Edmans et al., 2017). In the following, $\beta'(\tau)$ is the partial derivative of β with respect to τ, i.e. the predicted change according to the the quantile.

Hypothesis 1. *The short-term firm performance-pay relation increases in the quantile:*

[2]In the first specification, I do not take the log of shocks, but this is done in tables 6 and 7 in the appendix. Thus, the first specifications are for short-term incentives are %-\$-sensitivities.

β_1 is increasing in magnitude with τ, i.e. ($\beta_1'(\tau) > 0$), where $\beta_1 > 0$.

Hypothesis 2. *The long-term firm performance-pay relation decreases in the quantile: β_2 is decreasing in magnitude with τ, i.e. ($\beta_2'(\tau) < 0$), where $\beta_2 > 0$.*

Hypothesis 3. *The short-term industry performance-pay relation decreases in the quantile: β_3 is increasing in magnitude with τ, i.e. ($\beta_3'(\tau) < 0$), where $\beta_3 < 0$.*

Hypothesis 4. *The long-term industry performance-pay relation decreases in the quantile: β_4 is increasing in magnitude with τ ($\beta_4'(\tau) < 0$), where $\beta_4 < 0$.*

A conditional highly paid executive can potentially have a larger dollar gain from bargaining with the board over the variable pay in case of poor short-term firm performance. I expect managers in the upper tail to the conditional distribution to have a lower performance-pay elasticity if there is poor short-term firm performance. This motivates the second hypothesis. $\mathbf{I}\{Shock_{f,s} < 0\}$ is the indicator for a negative shock to firm's market value. The performance-pay relation at a given quantile with asymmetry for high and low short-term firm performance can be written as

$$Q_Y(\tau|X) = \beta_1 Shock_f + \beta_2 Trend_f + \beta_3 Shock_s + \beta_4 Trend_s + \beta_5 \mathbf{I}\{S_f < 0\} \cdot S_f. \quad (2)$$

Hypothesis 5. *Pay reacts more to positive than negative short-term changes in firm value: $\beta_5 < 0$, and $\beta_1 > 0$. The degree of asymmetry is increasing with τ, i.e. $\beta_1'(\tau) > 0$, and $\beta_5'(\tau) < 0$.*

3 Data

I now discuss the data and variables used in the study. I use compensation data from a 12 year unbalanced panel of executives in the C-suite of publicly listed firms for 40 countries over the years 2002-2013, provided by BoardEx. The data span across countries mainly consisting of the USA, UK, Western Europe and Scandinavia. The unit of observation is the pay of an executive i in a firm f for a given year t. There are a number of movers in the data, 183, which can be calculated by the difference in unique executive-firm matches, and the number of executives in the data altogether.[3] I include individuals that are executive directors in firms for which there is matching financial data acquired from the ORBIS database from Bureau van Dijk.

The main dependent variables of the study are total compensation and total wealth. Total compensation consists of salary and cash bonus plus the grant-date value of newly emitted equity-linked compensation (such as stock options, restricted stock awards), and long-term incentive plans (restricted bonuses paid out in the future) in each year, a measure used by Fernandes et al. (2013). The total compensation variable measures the grant-date opportunity cost to the shareholders of the executive's pay package (Fernandes et al., 2013). Executives not only receive pay and stock grants each year, but accumulate stock holdings and non-vested equity-linked pay. Firm performance can thus affect executive wealth to a larger degree than if one merely used yearly total compensation (Frydman and Jenter, 2010). The literature on executive compensation emphasizes that incentives for executives are stronger when using total wealth to measure pay(Jensen and Murphy, 1990). This justifies the use of total wealth as an outcome variable used to measure the strength of incentives (Edmans et al., 2017). Total wealth is calculated as the sum of estimated market value of cumulative holdings of stock(-related pay), in-the-money options, and long-term incentive plans for the executive (Fernandes et al., 2013).[4]

Market value of equity at year end is used to generate the main independent variables of the study.[5] This is used by other studies examining the wealth-performance relationship (Jensen and Murphy, 1990; Bertrand and Mullainathan, 2001). The long-term stock

[3]50% of executives are observed for 4 years in the data. The probability of an executive remaining in the sample for the following period is 0.78 on average. However, there is no time pattern in attrition rate, which indicates that attrition happens, but does not become more severe over time.

[4]The calculation of total wealth, as done by BoardEx is explained in more detail in appendix A.

[5]This variable is astk_market_cap in ORBIS.

price captures all potential outcomes of CEO behavior (e.g., changes in growth or profit, corporate restructuring) affecting shareholder value (Jensen, 2001; Edmans et al., 2017). The business cycle of each firm and each industry is modeled using the band-pass filter to separate the cyclical component of market values from the long-run trend for each firm, as done by DeVaro et al. (2017). I also control for the macroeconomic indicators GDP per capita, GDP-growth in percent, provided by the World Bank and inflation as the percentage change in average consumer prices, provided by the International Monetary Fund. These serve to control for time-variant country-level heterogeneity.

Although other studies control for firm size (Garvey and Milbourn, 2006), as larger firms can employ better qualified and better paid managers (Murphy, 1999); growth potential using the market-to-book ratio (DeVaro et al., 2017), leverage (DeVaro et al., 2017), and other variables, I decide explicitly not to include these controls, as they can likely cause biased estimates of coefficients. Including control variables that are simultaneously determined with the outcome variable of interest by the independent variables leads to this bias.[6]

3.1 Measuring Short-Term and Long-Term Performance

Short-term and long-term firm and industry performance is identified using the band-pass filter (Christiano and Fitzgerald, 2003), and is based on the theory of business cycles (Burns and Mitchell, 1947). This separates the performance, proxied by market value of a firm f or industry s at time t into a trend component $Trend$, and a cyclical

[6]For example, if performance affects the firm's market-to-book ratio, the relation between firm performance on compensation is not identified. The resulting bias can be shown in simultaneous equation system:

$$\begin{aligned} Pay &= \alpha + \rho \cdot Performance + \gamma \cdot GrowthPotential + e_i \\ GrowthPotential &= \lambda_0 + \lambda_1 \cdot Performance + u_i \\ Pay &= (\alpha + \gamma\lambda_0) + (\rho + \lambda_1) Performance + (u_i + e_i). \end{aligned}$$

component, $Shock$, so that

$$Market\ Value_{ft} = Shock_{ft} + Trend_{ft}. \tag{3}$$

This filter is also used to identify the effects of firm shocks on executive compensation in a different setting done by DeVaro et al. (2017). I apply it to the time series of the market value of each firm to generate the shocks of year end market value for each firm, and to the time series of the mean year-end shareholder wealth of the industry.

For the yearly data, I remove stochastic cycles that range from two to eight years, so $p_l = 2$ and $p_h = 8$. This is in accordance with Burns and Mitchell (1947), who define business cycles as stochastic cycles in business data between 1.5 and 8 years. Figures 1 and 2 show the application of the filter for the yearly data to a firm and an industry in the data, and that it works to identify changes in performance with mean zero. The firm and industry shock and trend variables $Shock_{f,s}$ and $Trend_{f,s}$ serve as the proxies for short-term and long-term firm performance and industry performance.

Although the shock variable has approximately mean zero and identifies a stochastic fluctuation, this could still be due to the firm's own productivity changes over the business cycle. This could be due to short-term oriented behavior or external factors. This is why I do not interpret short-term changes in firm performance as luck, but define it as 'short-term performance'. The trend component is defined as 'long-term performance.'

Table 1 describes the main variables of interest, using all observations from the final sample. An advantage of the data set is to be able to track executives over a long time frame. Further in the final sample, I have data from 40 countries, adding to the generality of the findings to outside the US, which has been the central focus in the literature hitherto.

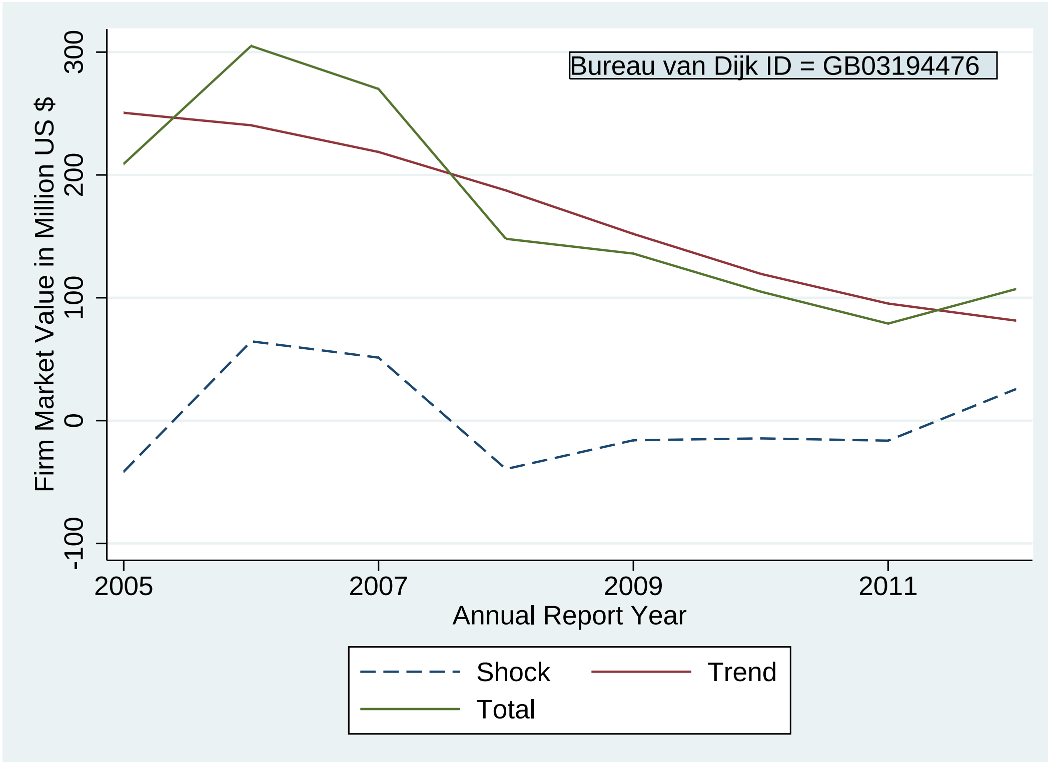

Figure 1: Business cycle of firm with ID GB03194476, showing the time series of market value, the cyclical and trend components from the band pass filter, removing cycles from 2 to 8 years and accounting for drift.

4 Empirical Framework

4.1 Method of Moments-Quantile Regression

I now discuss the application of the method of moments-quantile regression (MM-QR) as recently introduced by Machado and Santos Silva (2019). The intuition behind the methodology is simple: "In a conditional location-scale model, the information provided by the conditional mean and the conditional scale function is equivalent to the information provided by regression quantiles in the sense that these functions completely characterize how the regressors affect the conditional distribution." (Machado and Santos Silva, 2019). This makes it computationally easy to estimate a model with a large number of individual-specific fixed effects. In this study, I estimate over 8,000 individual-specific unobserved effects. In general, the aim is to identify the response of

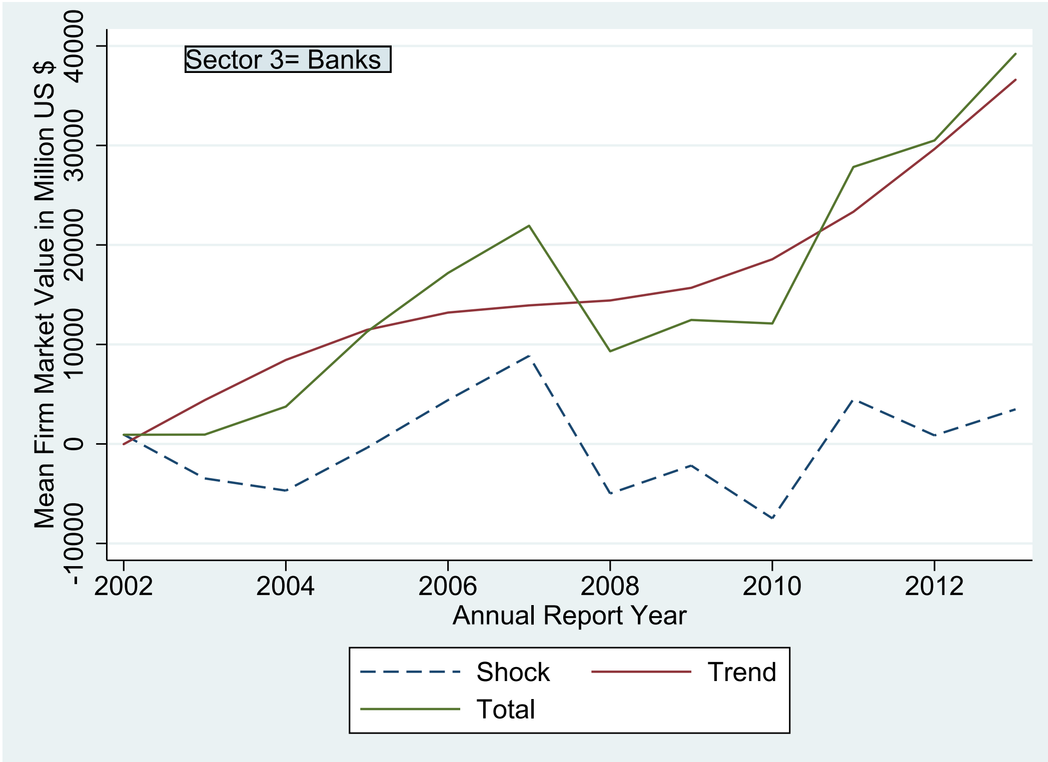

Figure 2: Business cycle of the banking sector, showing the time series of average market value for the sector, the cyclical and trend components from the band pass filter, removing cycles from 2 to 8 years and accounting for drift.

the compensation Y_{ift} of an executive i in a firm f at a certain point in time t, to a performance measure of firm f or industry s, as defined by X_{ft}, across the conditional distribution of pay. The response of compensation to performance is allowed to depend on the position of pay in the conditional distribution, which is modeled by unobserved noise U_{ift} distributed on the uniform interval $[0, 1]$. Thus I want to estimate

$$Y_{ift} = X'_{f,st}\beta(U_{ift}),\ i = 1, \ldots, n. \tag{4}$$

However, standard quantile regression methods do not deal with the panel nature of the data. This poses a problem for identification if we want to identify the effect, holding unobserved individual factors constant. If there are unobserved, time constant factors α_{if} affecting performance and pay, we have omitted variable bias. Accounting for this

Variable	N	Mean	S.D.	Min.	Max.	Skew.
Salary*	27,393	506.8	419.1	15.8	2,280.5	1.7
Bonus*	23,060	426.7	722.1	0.0	4,232.3	3.0
Equity linked*	14,565	2,075.4	4,393.7	2.9	30,025.0	4.4
Total compensation*	27,538	1,915.2	3,344.2	17.7	22,458.1	3.9
Total wealth*	24,008	15,564.4	52,726.0	4.7	418,808.2	6.1
Market value of equity**	32,377	6,476.4	15,966.4	3.0	97,129.0	3.9
Firm value shock***	32,377	0.0	2.4	-10.6	12.1	0.6
Firm value trend***	32,377	6.5	15.7	0.0	93.7	3.8
Industry shock***	32,377	0.1	2.3	-7.5	8.9	0.5
Industry trend***	32,377	6.7	6.2	0.5	30.8	1.6
GDP growth	31,814	1.1	2.6	-8.3	15.2	-0.7
GDP per capita	31,565	42,106.9	8,868.6	765.3	115,109.3	0.8
Inflation	31,565	2.5	1.3	-1.7	16.0	1.2

*** scaled in Billions $US, ** scaled in millions $US, * scaled in thousands $US. The sum of salary, bonus, grant-date value of newly emitted equity-linked and long term incentive plans, equals total compensation. Observations with zero salary or total compensation are dropped from the data, as this is entirely implausible. If an executive works in two firms at the same time, plausibility checks were done and some observations dropped according to the following criteria. If data is entirely missing, this observation is deleted. If there is a holding company or a subsidiary, and the executive had the same position at both firms, the observation belonging to the parent company is kept. If one position was only a representative or deputy position, this observation is deleted. If the firm is listed in two countries, the headquarter country is kept. If the executive switched positions and thus worked for two companies in one year, the first year of the new job is deleted, as this generally covers fewer months. All compensation and market value, shock and trend variables are winsorized at the 1st and 99th percentiles. Firm and industry shock and trend variables are generated using the band-pass filter, removing drift and cycles between 2 and 8 years from the raw data to generate the trend. GDP growth and GDP per capita are from the World Bank, and Inflation is measured as the average percentage change in consumer prices in each country, which is from the IMF database.

Table 1: Summary Statistics

would estimate the pay elasticity at the t'th quantile as

$$Q_Y(\tau|X) = \alpha_{if} + X'_{ft}\beta q(\tau), \tag{5}$$

where $q(\tau) = F_U^{-1}(\tau)$. This could be dealt with by including individual intercepts. However, including a large number of individual specific intercepts in the quantile regression is computationally burdensome. Further, variance estimates of other covariates may be increasingly large in proportion to the amount of fixed effects (Koenker, 2004). This is especially the case if we have a short panel, as standard errors for individual effects will be large.[7]

A second potential source of unobserved heterogeneity is in the conditional variance of pay. In case the conditional variance of pay depends on time-constant unobserved factors, not accounting for these can bias estimates of the conditional variance, if they are correlated with covariates and our outcome variable of interest. An unobserved individual specific factor of this description is the risk-tolerance of an executive. Undertaking riskier projects has an option value. This can lead to larger variance in firm outcomes, as well as a larger variance in employee pay. Further, more risk tolerant workers may make it to the top of large firms that pay well. The method applied accounts for unobserved differences in the conditional mean and the conditional variance of pay, using a location-scale model developed by Machado and Santos Silva (2019).

If we make the assumption that the location and scale functions are known, we can specify our empirical model of the relation between pay and covariates as

$$Y_{ift} = \alpha_{if} + X'_{ift}\beta + \sigma(\delta_{if} + X_{ift}\gamma)U_{ift} \tag{6}$$

where σ is the scale function. I assume the scale function to be linear in covariates. Here, regressors may only affect the distribution of the response variable through known location and scale functions (Koenker and Bassett Jr, 1982). However, heteroskedasticity may not be linear, but can be multiplicative (Godfrey, 1978; Koenker and Bas-

[7]To account for a location shift, which is independent of the quantile estimated, Koenker (2004) uses l_1 shrinkage methods to control for the large number of fixed effects. Other methods to only account for location shifts have been developed by Lamarche (2010) and Canay (2011).

sett Jr, 1982). In this case the scale-shift for a quantile q is not linear in covariates but quadratic in covariates, as shown in an example by Koenker (2005).[8] Thus, results should be taken with some caution, as they do not account for second or higher order changes in performance on pay.[9] I estimate

$$\hat{Q}_Y(\tau|X_{ift}) = (\hat{\alpha}_{if} + \hat{\delta}_{if}\hat{q}(\tau)) + X'_{ift}(\hat{\beta} + \hat{\gamma}\hat{q}(\tau)) + \hat{\varepsilon}_{ift}. \tag{7}$$

Estimates for coefficient of interest l are

$$\hat{\beta}_l(\tau, X) = \hat{\beta}_l + \hat{q}\hat{\gamma}. \tag{8}$$

The scale parameter γ is informative of heterogeneity in the coefficients of interest at a certain estimated quantile $\hat{q}$. The estimation procedure, outlined by Machado and Santos Silva (2019), is shortly described here. The average coefficients $\hat{\beta}$ in the MM-QR procedure are obtained by using OLS of time-demeaned independent and dependent variables, regressing $(Y_{it} - \sum_t Y_{it}/T)$ on $(X_{it} - \sum_t X_{it}/T)$. Then, the location shift $\hat{\alpha}_i$ is calculated from OLS esimtation as $\hat{\alpha}_i = \frac{1}{T}\sum_t(Y_{it} - X'_{it}\hat{\beta})$, which delivers the residuals $\hat{R}_{it} = Y_{it} - \hat{\alpha}_i - X'_{it}\hat{\beta}$. The scale parameter, $\hat{\gamma}$, showing effect heterogeneity is obtained by regressing the time-demeaned absolute value of residuals $(|\hat{R}_{it}| - \sum_t |\hat{R}_{it}|/T)$ on exogenous variables Z.[10] The conditional variance that is time-constant and unobserved is estimated analogously to above by $\hat{\delta}_i = \frac{1}{T}\sum_t(|\hat{R}_{it}| - Z'_{it}\hat{\gamma})$. The quantile $q(\tau)$ is then estimated by

$$\min_q \sum_i \sum_t \rho_\tau \left(\hat{R}_{it} - \left(\hat{\delta} + Z'_{it}\hat{\gamma} \right) q \right)$$

[8]A model where a single explanatory variable has a quadratic effect on the scale of the conditional distribution is, for example, $y_i = \beta_0 + \beta_1 x_i + (1 + x_i)^2 u_i$ (Koenker, 2005).

[9]Browsing the literature, most studies of performance-pay do not include polynomials of performance. I do not include polynomials to be in line with the literature, and keep results comparable.

[10]One may use an alternative transformation of residuals that has mean 0 conditional on Z. Here, Z is X in our setting.

to obtain esimates of quantiles $\hat{q}$ in the data, where ρ is the check function (Machado and Santos Silva, 2019). As the estimation procedure above shows, parameter estimates for coefficients of interest $\hat{\beta}$ and $\hat{\gamma}$ are unconditional on the executive-firm fixed effect $\hat{\alpha}(\tau) = \hat{\alpha}_{if} + \hat{q}_{if}\hat{\delta}_{if}$. We can make comparative static interpretations independent of executive ability or risk preferences. This gives a direct link to fixed effects regressions at the conditional mean: The location parameter identifies the effect at the conditional mean, so there is no need to estimate standard panel regression with fixed effects separately. A potential problem is that confidence intervals for scale parameters have poor coverage when n/T is large (Machado and Santos Silva, 2019). I bias-correct point estimates from main results in a robustness test in section 5.2, using the split-panel jackknife method introduced by Dhaene and Jochmans (2015) to mitigate this problem.[11]

5 Main Results

5.1 Total Compensation

Testing the hypotheses 1 to 4, I estimate regression quantiles of the logarithm of total compensation, $\log Y_{ift}$, of an executive i in a specific firm f at time t, on short-term firm and industry performance, $Shock_{ft}$ and $Shock_{st}$, the logarithm of long-term firm and industry performance, $\log Trend_{st}$ and $\log Trend_{ft}$, macroeconomic controls, and year indicators.[12] The fixed effect is an executive-firm pair effect. If an executive switches firms, another fixed effect is estimated. This accounts for all unobserved, time-constant

[11] Machado and Santos Silva (2019) show that the bias-corrected estimator performs far better than the uncorrected estimator for different panel lengths, and works reasonably well for a panel length of 10.

[12] I do not take the logarithm of shocks in the first specification, as these also take negative values. In tables 6 and 7 in the appendix, I transform shocks in a linear fashion to be positive and take the logarithm, to estimate an elasticity for each coefficient. Results remain similar, independent of the measure used.

heterogeneity between executive-firm matches. I estimate the equation

$$\hat{Q}_{\log Y_{ift}}(\tau|\cdot) = (\hat{\alpha}_{if} + \hat{\delta}_{if}\hat{q}(\tau)) + (Shock_{ft} + Shock_{st} + \log Trend_{ft} + \log Trend_{st} + \mathbf{X'}_{ft} + \psi_t)(\hat{\beta} + \hat{\gamma}\hat{q}(\tau)) + \hat{\varepsilon}_{ift} \quad (9)$$

using the unbalanced panel. I deal with missing data and serial correlation of pay by clustering standard errors via bootstrapping (Parente and Silva, 2016). Even if there is intra-cluster correlation, estimates of quantile regression are also consistent under certain conditions (Parente and Silva, 2016). I resample from each firm-executive cluster, with 50 replications. Location, scale and point estimates of coefficients of interest at the 10th, 30th, 50th, 70th, and 90th percentiles are reported in table 2.

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
$Shock_f$	-0.0024**	0.0084***	0.0121***	0.0104***	0.0083***	0.0066***	0.0049***
	(0.0010)	(0.0017)	(0.0029)	(0.0023)	(0.0016)	(0.0013)	(0.0012)
Log $Trend_f$	0.0160**	0.2016***	0.1769***	0.1887***	0.2026***	0.2144***	0.2255***
	(0.0075)	(0.0147)	(0.0202)	(0.0168)	(0.0146)	(0.0148)	(0.0168)
$Shock_s$	-0.0005	0.0009	0.0016	0.0013	0.0009	0.0005	0.0002
	(0.0011)	(0.0019)	(0.0028)	(0.0022)	(0.0019)	(0.0019)	(0.0022)
Log $Trend_s$	-0.0169	-0.0229	0.0032	-0.0092	-0.0239	-0.0364	-0.0480
	(0.0117)	(0.0249)	(0.0313)	(0.0270)	(0.0249)	(0.0263)	(0.0299)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Results show method of moments-quantile regressions of log(1+total compensation) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data. Compensation and performance variables are winsorized at the 1st and 99th percentiles.

Table 2: MM-QR of log total compensation on firm and industry performance measures

Testing hypothesis 1 in table 2, the coefficient of interest belongs to the variable $Shock_f$. Both location and scale parameters are estimated precisely in columns one and two. At the conditional median, one billion dollar increase in short term firm value is associated with an increase in pay of 0.83%. Equivalently, a one standard deviation increase firm shock ($2.4 billion, from summary statistics) leads to a 2% increase in pay. Although this sensitivity seems rather low, we must note that shock values are not scaled by firm size, so the pay-performance sensitivity is a %-$ relation. This can, for example, be interpreted as the disincentive to take perquisites, or the response of pay to an action that changes dollar firm performance. To identify effect heterogeneity, the scale parameter belonging to the short-term firm performance is of interest. The significant negative scale estimate shows that the sensitivity to a dollar change in short-term firm performance is a decreasing function of the quantile, and responds less for conditionally high paid executives. Thus, when using total yearly compensation as the measure for incentives, hypothesis 1 is rejected. Short-term performance pay sensitivity is increasing with the pay quantile.

To calculate an elasticity for pay and short term performance, I do a linear transformation of short-term firm performance $Shock + x$, where x is the smallest number such that all values are positive. I then take the logarithm, $\log(1 + (Shock_f + x))$. The elasticity between short-term firm performance and total compensation is monotonically decreasing across the conditional distribution, ranging from 0.094 at the 10th percentile to 0.030 at the 90th percentile (results in appendix table 6). The location parameter (0.062, p=0.001) and scale parameter (-0.0212, p=0.051) for short-term performance show significant heterogeneity for short-term performance-pay elasticity across the distribution. Summing up, the short-term firm performance-total compensation sensitivity is decreasing in the conditional quantile of total compensation.

Testing hypothesis 2, the coefficient of log $Trend_f$ in table 2 is of interest. This is the elasticity of total compensation to long-term firm performance is 0.20 at the median. Both location and scale parameters are estimated precisely, and the positive scale parameter shows that predicted earnings respond more to long-term changes in performance at the top of the conditional distribution. The elasticity is about 27% higher at the 90th percentile than the 10th percentile. The difference is statistically significant as the scale function shows. This is evidence rejects hypothesis 2 for total compensation. Summing up, the long-term firm performance-total compensation relation is increasing as we go up the distribution.

Testing hypothesis 3, there is no significant effect of industry short-term performance on total compensation. The estimate of the location parameter is close to zero, and normal-based 95%-confidence intervals using bootstrapped standard errors estimate the coefficient is between -0.0028 and 0.0046. Firms do not appear to benchmark in the short run against the industry. A possibility is that industry shocks mostly affect compensation by directly affecting firm performance in the short-term, as in Bertrand and Mullainathan (2001). The variation captured by the coefficient of short-term industry performance is residual variance not explained by firm performance. A stronger test of relative performance evaluation in a distributional framework could use a two-stage regression approach as done by (Bertrand and Mullainathan, 2001), or possibly structural quantile regressions (Machado and Santos Silva, 2019) if a valid instrument can be identified. Finding a valid instrument has proven to be difficult in the executive compensation literature (Edmans et al., 2017), although there are some promising recent advances (Ladika and Sautner, 2019).

Testing hypothesis 4, the coefficient of interest belongs to the the industry trend in table 2. The location parameter is imprecisely estimated, and the scale parameter is also imprecisely estimated. This is in line with the literature, as there is mixed evidence that firms use industry performance benchmarking (Edmans et al., 2017). I can not entirely rule out long-term industry benchmarking in line with relative performance evaluation, as estimates are noisy. Nevertheless, distributional approaches to investigate industry benchmarking in more detail seems a potential direction for future research. Summing up my findings from regressions using total compensation, incentives for executives are estimated to be more long-term oriented in the upper tail. Conditionally higher paid executives have relatively longer-term oriented incentives. I next test hypothesis 5, whether short-term firm performance-pay sensitivity is the same for high and low performance, and increasing in the quantile. This specification allows for different performance-pay sensitivities for high and low short-term performance, proxied by positive and negative shocks in the firm's market value. I estimate this using an analogous regression to above, with an added interaction $\mathbf{I}\{S_f < 0\}_{ft}$ indicating negative shock in firm f at year t, and run

$$\hat{Q}_{\log Y_{ift}}(\tau|\cdot) = (\hat{\alpha}_{if} + \hat{\delta}_{if}\hat{q}(\tau)) + (Shock_{ft} + \mathbf{I}\{S_f < 0\}_{ft} \times Shock_{ft} + Shock_{st} + \log Trend_{ft} + \log Trend_{st} + \mathbf{X'}_{ft} + \psi_t)(\hat{\beta} + \hat{\gamma}\hat{q}(\tau)) + \hat{\varepsilon}_{ift}. \quad (10)$$

Turning to estimation results in table 3, the location parameters for the coefficients of interest, $Shock_f$ and the interaction with the indicator for negative shocks, are not precisely estimated. This reveals no significant effect at the mean. There is a significant difference in the conditional variance of pay for negative shocks, but no point estimate is significant. Thus, we do not have significant evidence for an asymmetry in pay for positive and negative short term firm performance. A potential confound of not finding asymmetry in short-term performance-pay relation is executives being fired if they perform badly. However Campbell and Thompson (2015) find that asymmetry in performance-pay for good and bad firm performance is likely used as a retention device, as the asymmetry is stronger when labor market conditions are favorable for executives. This means the executive's outside option is higher and the firm must reward the manager more to retain her. Thus, even if some managers are fired, we should still expect to observe asymmetry in short-term performance-pay sensitivity.

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
$Shock_f$	0.0003	0.0057	0.0053	0.0055	0.0057	0.0059*	0.0061*
	(0.0016)	(0.0039)	(0.0057)	(0.0048)	(0.0038)	(0.0033)	(0.0032)
$\mathbf{I}\{S_f < 0\} \times S_f$	-0.0058*	0.0059	0.0149	0.0106	0.0056	0.0013	-0.0027
	(0.0032)	(0.0073)	(0.0105)	(0.0088)	(0.0072)	(0.0065)	(0.0065)
Log $Trend_f$	0.0156**	0.2021***	0.1781***	0.1895***	0.2030***	0.2145***	0.2253***
	(0.0078)	(0.0138)	(0.0194)	(0.0159)	(0.0137)	(0.0143)	(0.0168)
$Shock_s$	-0.0005	0.0009	0.0018	0.0014	0.0009	0.0005	0.0002
	(0.0012)	(0.0022)	(0.0033)	(0.0026)	(0.0022)	(0.0021)	(0.0024)
Log $Trend_s$	-0.0169	-0.0229	0.0032	-0.0092	-0.0239	-0.0364	-0.0481
	(0.0123)	(0.0243)	(0.0320)	(0.0269)	(0.0242)	(0.0255)	(0.0293)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Results show method of moments-quantile regressions of log(1+total compensation) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data. Compensation and performance variables are winsorized at the 1st and 99th percentiles. $\mathbf{I}\{S_f < 0\}$ takes value one if the shock in that year was negative, and zero otherwise.

Table 3: MM-QR of log total compensation on firm and industry performance measures with asymmetry

5.2 Executive Wealth

One potential source of measurement error introduced by using total compensation as a measure of pay, is due to the use of long-term incentive plans, and stock-related pay (like stock options and restricted stock awards) by firms (Frydman and Jenter, 2010). Firms grant executives stock-related pay over a successive number of periods that eventually vests. The stock related pay holdings react mechanically with the stock price, which is not the case for salary and cash bonus.

I test whether results are similar when using the logarithm of an executive's total wealth as a measure of pay. Results are shown in table 4. Testing hypothesis 1, the coefficient of interest is $Shock_f$. The location and scale parameters are precisely estimated, and the scale parameter shows the short-term performance-wealth sensitivity is increasing in the distribution. At the median, a one billion dollar increase in short-term performance correlates with a 1.43% increase in pay. Equivalently, a one standard deviation increase in short-term performance ($2.4 billion) correlates with a 3.4% increase in pay, which is higher than the associated sensitivity calculated using total compensation at the median. Further, this sensitivity increases to 4.3% at the 90th percentile. These estimates are for dollar changes in firm value, and are a lower bound, as they measure incentives for dollar changes in firm value on executive wealth. In table 7 of the appendix, I measure the associated elasticity of log wealth to short-term performance, which ranges from 0.05 at the 10th percentile, to 0.11 at the 90th percentile. This is a statistically and economically significant increase of over 100%. Importantly, this result is in contrast using total compensation as the measure of pay, and supports hypothesis 1.

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
$Shock_f$	0.0030***	0.0139***	0.0092***	0.0115***	0.0143***	0.0164***	0.0182***
	(0.0011)	(0.0023)	(0.0033)	(0.0027)	(0.0023)	(0.0021)	(0.0022)
Log $Trend_f$	-0.0282***	0.7551***	0.7994***	0.7778***	0.7520***	0.7316***	0.7150***
	(0.0105)	(0.0338)	(0.0389)	(0.0356)	(0.0336)	(0.0341)	(0.0357)
$Shock_s$	-0.0045***	0.0036	0.0107**	0.0072**	0.0032	-0.0001	-0.0027
	(0.0015)	(0.0031)	(0.0044)	(0.0037)	(0.0030)	(0.0029)	(0.0031)
Log $Trend_s$	-0.0202	-0.0365	-0.0048	-0.0203	-0.0387	-0.0533	-0.0652
	(0.0173)	(0.0453)	(0.0564)	(0.0494)	(0.0451)	(0.0454)	(0.0481)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Results show method of moments-quantile regressions of log(1+total wealth) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data. Compensation and performance variables are winsorized at the 1st and 99th percentiles.

Table 4: MM-QR of log total wealth on firm and industry performance measures

Testing hypothesis 2 with total wealth as the dependent variable, the coefficient of interest belongs to log $Trend_f$, which measures long-term firm performance. The location and scale parameters are estimated precisely, and show that incentives for long-term performance are much stronger than for total compensation. A 1% increase in firm performance is associated with a 0.75% increase in total wealth at the conditional median, compared to 0.2% when using total compensation as the dependent variable. This finding is in line with the literature on incentives, which shows that they are generally larger when using total wealth as the dependent variable (Edmans et al., 2017). This is largely due to the accumulation of equity-based pay over time, which makes up a large part of compensation packages (Frydman and Jenter, 2010; Edmans et al., 2017). Further, the incentive strength to maximise long-term shareholder wealth is decreasing in the conditional quantile, as the negative scale parameter for the coefficient of $\log Trend_{ft}$ shows. A 1% increase in long-term firm performance is associated with an 0.8% increase in total wealth at the 10th percentile, and reduces to 0.72% at the 90th percentile.

When retesting predictions 3-5 using total wealth, the results differ slightly. The estimates of the location parameter for industry shocks and trends is again noisily estimated, but point estimates show a positive correlation of executive pay and industry shocks for the lower tail.

5.3 Robustness of Results

In tables 8 and 9 of the appendix, I replicate the results from table 2 and 4 with bias-corrected point estimates. This is done using the split-panel jackknife bias correction developed by Dhaene and Jochmans (2015), where the panel is split into even and odd years. Only executive-firm matches with at least 6 observations are used to estimate the bias. The results deliver qualitatively similar estimates as above for short-term and long-term firm performance, but the differences in coefficients across the distribution are larger in magnitude. This supports the economic significance of the findings.

Interestingly, I do find evidence for long-term relative performance evaluation of total compensation against the long-term industry performance in the upper tail of the distribution, when using the bias-correction in table 8. The point estimate for the long-term industry trend when using wealth is similar but insignificant. Further, the point estimate for wealth's response to short-term industry performance shows that executives' pay in the lower tail is positively correlated with term term industry performance and this becomes negative at the top of the conditional distribution. These results can potentially be explained by conditionally higher paid managers being rewarded more for outperforming the industry.

A potential endogeneity concern is that I cannot rule out self-selection into a contract. In my estimation, the difference in pay across the distribution that is time-constant and unobserved is accounted for. This likely accounts for a large amount unobserved differences across the distribution of executive pay and wealth that causes differences in pay levels. Empirical results, and assignment models of CEOs to firms support the interpretation that some managers earn more than others because more talented managers can run larger firms (Gabaix and Landier, 2008; Edmans and Gabaix, 2016; Edmans et al., 2017). I argue that this form of managerial talent is largely time-constant, and is accounted for by the executive-firm fixed effect. Thus, self-selection via managerial talent should not entirely drive the differences of pay across the conditional distribution. This is one major advantage of my econometric approach.

6 Discussion and Conclusion

Why do I find total compensation is more long-term oriented in the upper tail of the distribution, but total wealth reacts more to short-term performance in the upper tail of the distribution? One potential explanation is that total pay can be easliy adjusted by the firm to account for short-run and long-run performance in each period, but accumulated wealth, mostly consisting of stock-related pay cannot be easily adjusted. Wealth can only be changed if there are contractual means to restrict the payout to certain conditions, or regain already granted stock-related pay in certain cases, discussed below. In the US, claw-back clauses that can recover pay in case of fraud are written in law, but these can not prevent short-term behavior that is *legal*, such as investment choice.[13] There are a number of contractual measures used by firms to align executives' incentives with the long run shareholder wealth. The lengthening of the vesting period for restricted stock awards and stock-options, ties executive utility to future firm performance, even after the executive has left (Edmans et al., 2012, 2017). This may come at a cost for the firm, as lengthening the vesting period increases the risk of a good payout in case this extends long into retirement, so an upward adjustment of the base-pay may be necessary (Edmans et al., 2017). Further, the performance period of performance-based-equity can also be lengthened. The use of these mechanisms in my data go unobserved, so I cannot make a general statement about how efficient equity-linked pay is across the distribution. The main takeaway is that optimal vesting periods for equity-linked pay and the performance periods for performance-based equity dramatically differs for executives across the conditional distribution.

I add to the small literature on the distribution of incentives for executives. Conditionally wealthier executives' holdings react more to short-term changes, and less to long-term changes in shareholder wealth compared to conditional low earners, giving them more myopic incentives. I find no evidence for asymmetry in pay for luck across the conditional wage distribution. Future literature should disentangle the effects of different corporate governance policies on performance pay, and how this differs for lower and higher paid executives.

[13]The Dodd-Frank Act of 2010 and the Sarbanes-Oxley Act of 2002 in the US enable firms to regain payments after fraud, even if the executive is not charged. This is implemented by the SEC (Edmans et al., 2017).

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Appendix 1: Total Wealth

The total wealth variable is calculated by BoardEx. The closing stock price of the annual report date is used. They implement a Black-Scholes option pricing model. Volatility is measured using 100 days of historic stock prices. The risk free rate is measured using the following: UK = 6 months Libor rate, Europe = EURIBOR, US = 10 year T-Bill, otherwise = 6.5% It is assumed that exercise is on expiry date whether known or assumed.

Appendix 2: The Band-Pass Filter

I now look at the random walk approximation as described by Christiano and Fitzgerald (2003) used to generate shock and trend variables, the proxies for short and long-term firm performance. Assuming the ideal band-pass filter generates the data y_t when applied to raw data x_t, and the data generated from the approximation yield $\hat{y}_t$, then the problem of getting the best approximation minimizes the mean squared error between the ideal filter and the approximation:

$$E\big[(s_t - \hat{s}_t)^2 \mid y\big], \quad y \equiv [y_1, \cdots, y_t]. \tag{11}$$

The ideal filter generates the cyclical component using

$$s_t = \sum_{j=-\infty}^{\infty} b_j y_{t-j}. \tag{12}$$

So $\hat{s}_t$ is a linear projection of s on y in each t. The aim is to identify a part of y_t that oscillates with a period between p_l and p_h, where $2 \leq p_l < p_h < \infty$, using the random walk filter in the non-stationary asymmetric case (see Christiano and Fitzgerald 2003). The filter works for non-stationary data in that it is robust up to one unit root, but it is not invariant to drift as well (Christiano and Fitzgerald, 2003). One must remove drift so that the filter induces stationarity. Assuming a random walk plus drift process transforms the original series using

$$z_t = y_t - \frac{(t-1)(y_t - y_1)}{(T-1)}. \tag{13}$$

Appendix 3: Additional Tables

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
$Shock_f$	0.0068***	0.0132***	0.0025	0.0077	0.0139***	0.0189***	0.0229***
	(0.0026)	(0.0047)	(0.0060)	(0.0050)	(0.0047)	(0.0053)	(0.0062)
$\mathbf{I}\{S_f < 0\} \times S_f$	-0.0083*	0.0016	0.0146	0.0083	0.0007	-0.0053	-0.0102
	(0.0046)	(0.0088)	(0.0126)	(0.0103)	(0.0087)	(0.0089)	(0.0099)
Log $Trend_f$	-0.0288**	0.7552***	0.8005***	0.7784***	0.7520***	0.7312***	0.7142***
	(0.0115)	(0.0296)	(0.0347)	(0.0309)	(0.0296)	(0.0312)	(0.0339)
$Shock_s$	-0.0046***	0.0037	0.0109**	0.0073*	0.0031	-0.0002	-0.0029
	(0.0015)	(0.0032)	(0.0049)	(0.0040)	(0.0031)	(0.0026)	(0.0025)
Log $Trend_s$	-0.0205	-0.0364	-0.0042	-0.0199	-0.0387	-0.0535	-0.0656
	(0.0174)	(0.0487)	(0.0621)	(0.0543)	(0.0482)	(0.0468)	(0.0482)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Results show method of moments-quantile regressions of log(1+total wealth) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data. Compensation and performance variables are winsorized at the 1st and 99th percentiles. $\mathbf{I}\{S_f < 0\}$ takes value one if the shock in that year was negative, and zero otherwise.

Table 5: MM-QR of log total wealth on firm and industry performance measures with asymmetry

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
Log $Shock_f$	-0.0212***	0.0618***	0.0945***	0.0789***	0.0606***	0.0449***	0.0303***
	(0.0077)	(0.0125)	(0.0217)	(0.0168)	(0.0123)	(0.0104)	(0.0114)
Log $Trend_f$	0.0162*	0.2020***	0.1770***	0.1890***	0.2029***	0.2149***	0.2261***
	(0.0095)	(0.0184)	(0.0252)	(0.0209)	(0.0184)	(0.0188)	(0.0215)
Log $Shock_s$	-0.0087	0.0091	0.0226	0.0161	0.0086	0.0021	-0.0039
	(0.0069)	(0.0156)	(0.0209)	(0.0178)	(0.0155)	(0.0153)	(0.0166)
Log $Trend_s$	-0.0193	-0.0208	0.0090	-0.0052	-0.0218	-0.0361	-0.0494
	(0.0117)	(0.0271)	(0.0338)	(0.0294)	(0.0271)	(0.0280)	(0.0311)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Results show method of moments-quantile regressions of log(1+total compensation) on firm, and industry shocks ((log(1 + ($Shock_f + x$)), where x is the smallest number such that all values are non-negative) and log(1+trend)) and log(1+trend), with executive-firm fixed effects. Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data. Compensation and performance variables are winsorized at the 1st and 99th percentiles.

Table 6: MM-QR of log total compensation on firm and industry performance measures: Transformed shocks

	(1) Scale	(2) Location	(3) Q10	(4) Q30	(5) Q50	(6) Q70	(7) Q90
Log $Shock_f$	0.0210**	0.0844***	0.0514**	0.0675***	0.0866***	0.1019***	0.1142***
	(0.0089)	(0.0165)	(0.0223)	(0.0184)	(0.0165)	(0.0176)	(0.0201)
Log $Trend_f$	-0.0281**	0.7550***	0.7992***	0.7777***	0.7520***	0.7315***	0.7150***
	(0.0121)	(0.0371)	(0.0443)	(0.0398)	(0.0369)	(0.0368)	(0.0384)
Log $Shock_s$	-0.0230**	0.0379**	0.0739**	0.0564**	0.0354**	0.0187	0.0053
	(0.0101)	(0.0184)	(0.0297)	(0.0235)	(0.0179)	(0.0161)	(0.0170)
Log $Trend_s$	-0.0203	-0.0265	0.0053	-0.0102	-0.0287	-0.0435	-0.0554
	(0.0168)	(0.0526)	(0.0645)	(0.0575)	(0.0522)	(0.0510)	(0.0521)
N	32,377	32,377	32,377	32,377	32,377	32,377	32,377

Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Results show method of moments-quantile regressions of log(1+total wealth) on firm, and industry shocks ((log$(1 + (Shock_f + x))$, where x is the smallest number such that all values are non-negative) and log(1+trend)) and log(1+trend), with executive-firm fixed effects. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data, and compensation and market value of equity, as well as shocks are winsorized at the 1st and 99th percentiles.

Table 7: MM-QR of log total wealth on firm and industry performance measures: log of transformed shocks

	(1) Q10	(2) Q30	(3) Q50	(4) Q70	(5) Q90
$Shock_f$	0.0172***	0.0129***	0.0080***	0.0040**	0.0001
	(0.0030)	(0.0024)	(0.0017)	(0.0017)	(0.0015)
Log $Trend_f$	0.1397***	0.1698***	0.2045***	0.2331***	0.2610***
	(0.0245)	(0.0179)	(0.0143)	(0.0169)	(0.0169)
$Shock_s$	0.0030	0.0020	0.0008	-0.0002	-0.0011
	(0.0031)	(0.0031)	(0.0025)	(0.0024)	(0.0029)
Log $Trend_s$	0.0228	0.0006	-0.0250	-0.0461*	-0.0667**
	(0.0353)	(0.0252)	(0.0232)	(0.0263)	(0.0289)
N	32,377	32,377	32,377	32,377	32,377

This table shows bias-corrected estimates of coefficients estimated in table 2. This is done using the split-panel jackknife bias correction by Dhaene and Jochmans (2015), where the panel is split into even and odd years, and only executive-firm matches with at least 6 observations are used to estimate the bias. Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Results show method of moments-quantile regressions of log(1+total compensation) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data, and compensation and market value of equity, as well as shocks are winsorized at the 1st and 99th percentiles.

Table 8: Bias-corrected estimates of total compensation-performance sensitivities.

	(1) Q10	(2) Q30	(3) Q50	(4) Q70	(5) Q90
$Shock_f$	0.0046	0.0093***	0.0146***	0.0188***	0.0223***
	(0.0030)	(0.0023)	(0.0026)	(0.0024)	(0.0024)
Log $Trend_f$	0.8742***	0.8143***	0.7469***	0.6921***	0.6478***
	(0.0360)	(0.0334)	(0.0319)	(0.0393)	(0.0387)
$Shock_s$	0.0183***	0.0109***	0.0026	-0.0041	-0.0096***
	(0.0042)	(0.0040)	(0.0032)	(0.0030)	(0.0029)
Log $Trend_s$	-0.0047	-0.0207	-0.0386	-0.0533	-0.0651
	(0.0524)	(0.0457)	(0.0472)	(0.0542)	(0.0509)
N	32,377	32,377	32,377	32,377	32,377

This table shows bias-corrected estimates of coefficients estimated in table 4. This is done using the split-panel jackknife bias correction by Dhaene and Jochmans (2015), where the panel is split into even and odd years, and only executive-firm matches with at least 6 observations are used to estimate the bias. Results show method of moments-quantile regressions of log(1+total compensation) on firm, and industry shocks (scaled in billions for the estimation) and log(1+trend), with executive-firm fixed effects. Standard errors clustered at executive-firm level via bootstrap (50 reps) in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$. Full set of controls: GDP, GDP growth, inflation, and year dummies used. Controls not reported. Data set used is the full unbalanced panel from BoardEx executive compensation database, ORBIS for market value variables, and span 2002-2013 and 40 countries. GDP growth and GDP per capita are from the World Bank, and Inflation is from the IMF database. Observations with zero total compensation or base salary are removed from data, and compensation and market value of equity, as well as shocks are winsorized at the 1st and 99th percentiles.

Table 9: Bias-corrected estimates of total wealth-performance sensitivities.