Glass Floors and Ceilings:

Why Closing the Median Wage Gap Isn't Fair

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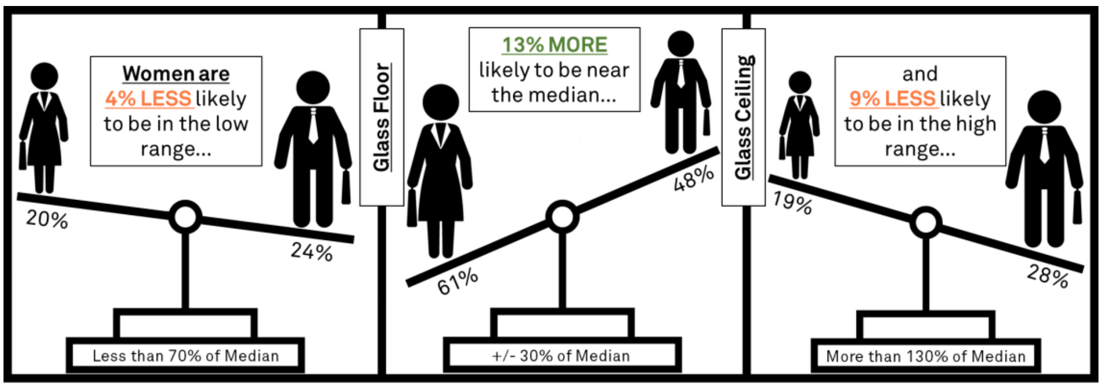
The gender wage gap describes the disparity in compensation between women and men doing the same work. Progress on this issue is commonly measured by comparing the median compensation for women to men. This research demonstrates that firms are catering to the focus on median compensation and are paying women in a tighter range around the median, compared to men in equivalent positions. Effectively, women have been given a glass floor as redress for the still-present glass ceiling. This 'Gender-Based Compensation Management' not only undermines the goal of equitable pay; but because the high end of the compensation range can be much farther from the median than the low end, this paradigm is a net disadvantage for women.

Figure 1: Women Given a Glass Floor as Redress for the Glass Ceiling[1]



Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

- Compared to men, women in executive roles are more likely to receive compensation in a compressed range around the median of their peer group and are less likely to receive compensation outside this range. The practice of **Gender-Based Compensation Management (GBCM)** artificially addresses the gender pay gap by increasing the median woman's compensation without providing women equal access to the full range of compensation. This work shows GBCM has exacerbated the 'glass ceiling' and, by extension, the gender disparity in compensation.

- Firms that have been defendants in federal court cases involving compensation disputes, discrimination, fraud, or other governance-related affairs exhibit more pronounced GBCM. This finding suggests **GBCM is associated with poor governance.**

- The percentage of women holding positions across the C-suite, board of directors, and executive positions grew from 15.4% to 19.2% from 2018 to 2020. While this progress is statistically meaningful, at this rate **women have at least 1-2 more decades before they reach parity in their representation across senior roles.** In positions where women's progress has been slower, such as CEO, parity will likely take even longer.

[1] Figure 1 analysis is for board members and executives affiliated with firms in the Russell 3000 as of year-end 2020. See section 8.1 for detailed methodology.

1. Background

To their own detriment, firms under-employ women in executive roles. Women in CEO and CFO roles deliver superior performance when compared to their male peers (Sandberg 2019). Companies with strong board networks[2] are more likely to have at least one woman as a board member and are more likely to proactively address gender diversity issues (Oyeniyi 2021). Despite the cited benefits, women remain underrepresented in senior roles.

Women that do secure senior roles have been compensated below their male peers, according to a 2010 report by the U.S. Government Accountability Office (Sherril 2010). Since 2010, the gender pay gap has received considerable attention from both academia (Gupta 2018, Hill 2014, Kang 2021) and the business community (Frank 2020, Kishan 2020). According to one survey (Payscale 2021), more than 75% of organizations have committed to a compensation philosophy and plan to purchase benchmark data to help set pay. The concerted effort has improved some metrics enough to lead researchers to conclude the gender pay gap is no longer statistically significant for some roles (Bugeja 2012, Gupta 2018). However, managing women's compensation using benchmarks can have unintended consequences, particularly if the benchmarks are not applied uniformly across genders.

This work shows the disproportionately stringent application of benchmarks to women's compensation has exacerbated the gender disparity in compensation.

2. Gender-Based Compensation Management (GBCM)

Throughout this section, executive compensation is represented as a ratio of actual compensation to a benchmark compensation value.

$$Pay\ Ratio = \frac{Actual\ Executive\ Compensation}{Benchmark\ Executive\ Compensation} \qquad \text{Eqn. 1}$$

By construction, the median pay ratio across all executives is exactly \$1.00. Pay ratios closer to \$1.00 should be interpreted as compensation closer to the median of the executive's peer group, accounting for differences in compensation across: 1) job functions, 2) business types[3], 3) company size, 4) the age and 5) tenure of the executive, and 6) executives that hold multiple positions.[4]

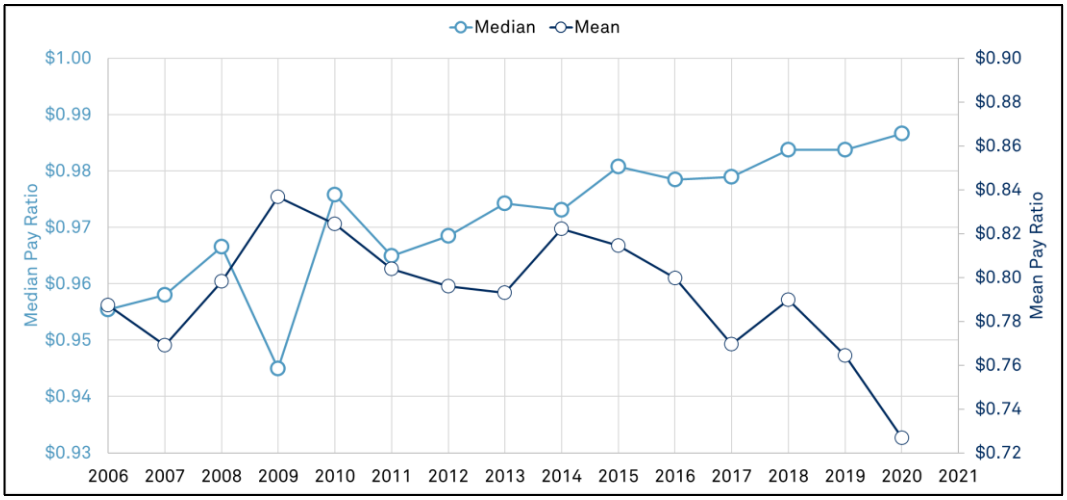
2.1. Conflicting Progress on Closing the Gender Pay Gap

One way to characterize the compensation received by women is to study the midpoint, or median, among the subset of executives that are women. The median is an attractive proxy for the 'typical value', because it is less sensitive to outliers and, by construction, half the women earn more and half the women earn less. Because of these benefits, this value is widely reported in studies of the gender pay gap. The analysis presented herein finds the

[2] Companies with directors who serve on more than one corporate board are well-connected (strong).
[3] Businesses were grouped by the Global Industry Classification Standard (GICS) taxonomy at the 4-digit Industry Group level.
[4] Full methodology details are presented in section 8.1, along with robustness analyses in sections 8.2 - 8.6.

women's median pay ratio has been steadily increasing over the 15-year study period and is between \$0.98 and \$0.99 as of 2020 (in agreement with values reported by Payscale 2021).

Figure 2: Median and Mean Pay Ratio, Russell 3000 Executive Women, 2006-2020



Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Another informative measure of central tendency is the mean, which is equivalent to an observation-weighted sum. Regardless of how the total compensation is distributed among the women in the study, the mean remains unchanged. Therefore, the benefit of the mean is that it provides the total value of compensation given to the entire cohort of women, controlling for changes in the number of women in the study over time. The $Mean\ Pay\ Ratio$, defined in eqn. 2, measures the entire cohort of women's compensation in comparison to the same for men,

$$Mean\ Pay\ Ratio = \frac{\overline{Pay\_Ratio_{Women}}}{\overline{Pay\_Ratio_{Men}}} \qquad \text{Eqn. 2}$$

where $\overline{Pay\_Ratio_{Women}}$ ($\overline{Pay\_Ratio_{Men}}$) is the arithmetic average pay ratio among women (men), calculated at each year-end.

In contrast to the median, the mean pay ratio has been declining over most of the study period. **Paradoxically, from 2006 to 2020, the individual woman earning the middle compensation among all women is more in line with her male counterpart (from \$0.95 to \$0.99); however, all women collectively are earning less than all men collectively (from \$0.78 to \$0.73).**

Considering the results from these analyses, the women's pay gap is not well explained by measures of central tendency[5]. However, much of the previous literature on the subject utilizes these measures, which may result in misleading conclusions.

[5] Section 8.6 explores an alternative approach using linear regression modeling that reaches similar conclusions to those presented in this section.

2.2. A Glass Floor as Redress for the Glass Ceiling

In the previous section, common techniques for distilling the gender pay gap into a single number (e.g., the median or mean) were shown to lead to conflicting conclusions. Instead of oversimplifying to a single value, figures 3 and 4 detail the full distribution of pay ratios and gender differences therein, respectively.

Figure 3: Distribution of Pay Ratios by Gender, Russell 3000 Executive Roles, 2020

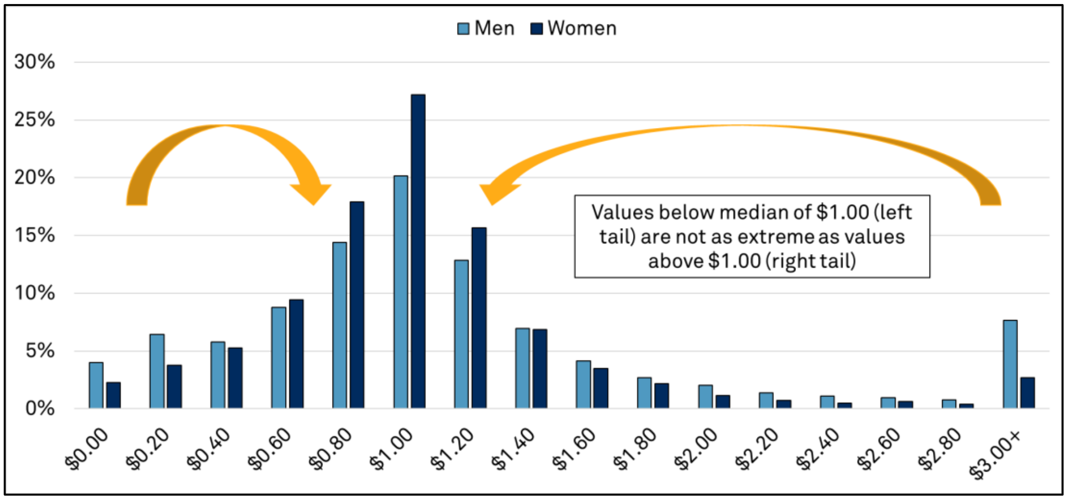
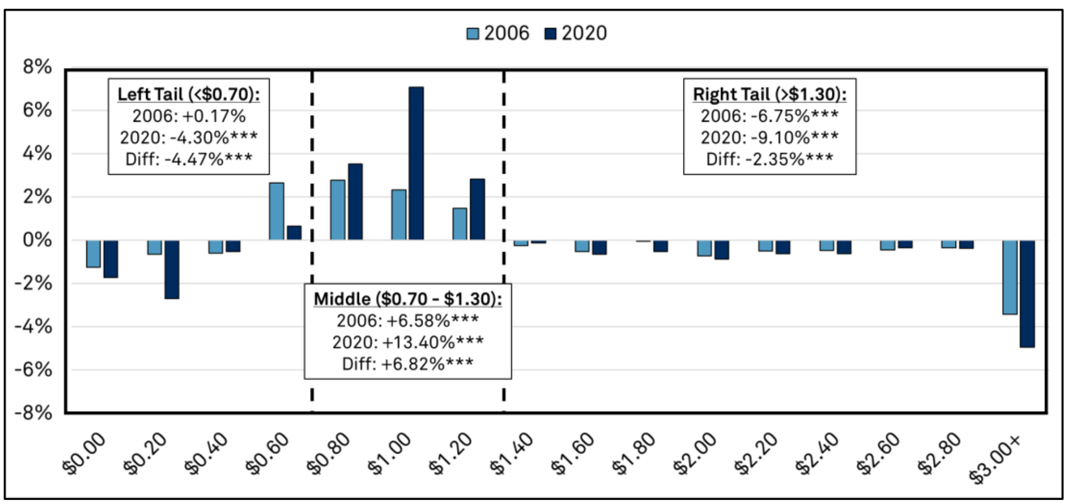


Figure 4: Gender-Based Differences in Pay Ratio, Russell 3000 Executives, 2006 and 2020



*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Source (Fig 3 and 4): S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Figure 4 shows how women are compensated relative to men, where true parity in pay would have all bars equal to 0%. Instead, relative to men, women are overrepresented in pay around their benchmark (pay ratios of $0.70 - $1.30) and underrepresented elsewhere. One explanation[6] for the relative difference in compensation is that **firms are giving more (less) aggressive raises to women in the low (high) compensation range relative to men, to push median compensation towards the benchmark for women while subsidizing the cost of pay raises.** This compensation paradigm is termed, **Gender-Based Compensation Management (GBCM).**

GBCM is less pronounced in the earlier part of the study horizon; particularly in the left tail of the distribution. Figure 4 shows that women were slightly more likely to be compensated below 70% of their peer group median (pay ratio of less than $0.70) in 2006. By 2020, women were 4.3% less likely to be compensated in this range. The 'glass floor' denotes this underrepresentation of women in the left tail of the compensation range. Likewise, women's representation in compensation above 130% of their peer group median (pay ratio of more than $1.30) has also declined. Though women were underrepresented in this range in 2006 by 6.8%, their representation declined by an additional 2.4% over the study period.

A migration of compensation from the tails to the middle of the distribution explains the paradoxical results presented in the previous section. As more women are paid in the middle of the distribution near $1.00, the median for women's pay will approach $1.00. However, the growth of the median value was not achieved by a wholesale move higher for women's compensation. Women are less likely to receive compensation at both the low and high end, where the high end of the pay spectrum is disproportionately farther away from the mid-point. Because compensation can extend much higher than the midpoint but is range bound on the low end, taking from both extremes in favor of the middle reduces the compensation that women in aggregate are earning. Consequently, the mean and the median diverge.

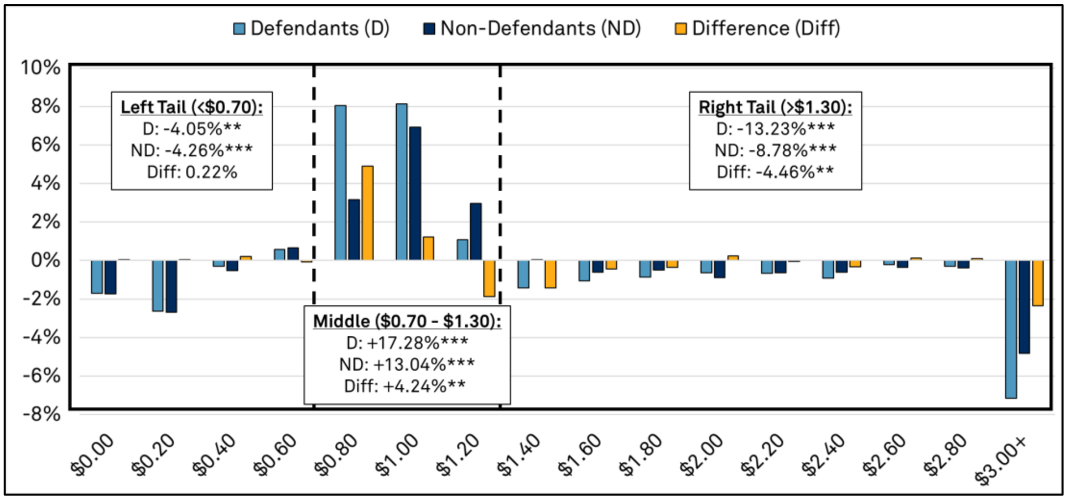
The mindset has long been that parity between median compensation for men and women indicates the absence of a gender bias. However, this work implies the commonly watched median compensation produces misleading conclusions. GBCM suggests **median compensations can align without women having the same access to the upper tier of compensation**. The glass floor is inequitable redress for the glass ceiling, which still exists in this paradigm.

3. Is GBCM Poor Governance?

GBCM is characterized by compensating women closer to a peer group median[7], or benchmark, than their male counterparts. A recent survey (Payscale 2021) on compensation best practices suggested that a majority of organizations procure compensation benchmark data in an effort to "ensure fair pay". One hypothesis for the emergence of GBCM over the 15-year study period, is the disproportionate application of these benchmarks to women compared to men.

[6] Section 8.5 explores an alternative hypothesis based on women's attrition from Russell 3000 executive positions, which is empirically rejected in favor of the explanation presented in this section.
[7] See section 2 for a high-level discussion or section 8.1 for detailed methodology.

Figure 5: Gender-Based Differences in Pay for Defendants in Select Federal Court Cases and Non-Defendants, Russell 3000 Firms, 2020



*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Firms that have been listed as defendants in federal court opinions involving compensation disputes, discrimination allegations, workplace affairs, or other governance topics (defendant firms) proxy inequitable corporate cultures. Women employed at both defendant firms and non-defendant firms are compensated more often in the middle of the distribution, and less in both tails, compared to their respective male counterparts. However, GBCM characteristics are more pronounced at defendant firms. While women are less likely to earn above their benchmark in both groups, the disparity is larger among defendant firms than non-defendant firms (-13.2% vs. -8.8%) by a statistically significant difference of almost 4.5%. The additional underrepresentation of women in the right tail is entirely balanced by an additional overrepresentation of women in the middle of the distribution. Consequently, women at defendant firms are 17% more likely than men to be compensated near the benchmark. There was no statistical difference noted below the benchmark of the compensation distribution between defendant and non-defendant firms. **The more pronounced GBCM effect among defendant firms compared to non-defendant firms suggests an association between GBCM and poor governance.** [8]

4. Progress in the Women's Representation Rate across C-Suite, Board of Directors, and Executive Positions

An underrepresentation of women in executive positions has been recognized since before 1986, when the term 'Glass Ceiling' was coined (Hymowitz 1986). Women's progress in penetrating these male-dominated roles has been slow and the women's representation rate (WRR), defined as the percentage of women, in senior roles remains far from parity[9] with men.

[8] Expanded discussion, including complete methodology and additional analysis, is provided in section 8.7.
[9] The framework used in this research assumes gender is a binary classification into 'men' and 'women'. Consequently, parity would be a 50% WRR. The modern vernacular for gender includes gender non-conforming or

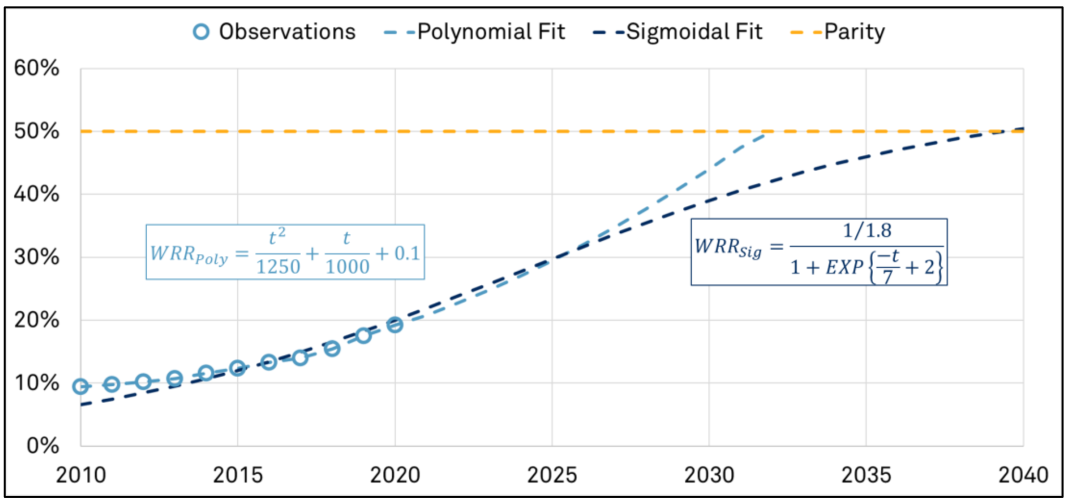
Across senior roles, the WRR has increased by more than 1% per year since 2018. However, at just 19.2% as of year-end 2020, WRR has much farther to go.

Table 1: Women's Representation in Select Senior Roles, Russell 3000, 2018-2020

Position	Cumulative 2yr Change	Women's Representation Rate			Avg Annual Exec Count (2018-2020)
		Y2020	Y2019	Y2018	
Board of Directors	5.0%***	23.5%	21.4%	18.5%	26,113
Chairman of the Board	1.4%***	5.7%	5.2%	4.3%	2,911
Secretary	2.3%**	21.8%	20.5%	19.5%	1,597
Treasurer	1.8%**	13.6%	13.1%	11.7%	820
Chief Executive Officer	0.5%*	5.5%	5.7%	5.0%	2,946
Chief Financial Officer	2.1%***	13.4%	12.0%	11.3%	2,827
Chief Operating Officer	1.7%**	10.6%	9.6%	8.9%	1,306
Chief Legal Officer	2.9%***	27.4%	24.7%	24.5%	1,296
Chief Accounting Officer	1.1%	15.0%	14.8%	13.9%	707
Chief Administrative Officer	3.5%*	27.9%	24.3%	24.3%	279
Chief Technology Officer	3.0%**	10.8%	8.1%	7.9%	247
Unit President / CEO	1.5%**	7.6%	7.5%	6.1%	1,133
ALL	**3.8%*** **	**19.2%**	**17.6%**	**15.4%**	**42,182**

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Figure 6: Women's Representation Rate in Executive Positions, Russell 3000, 2010-2020 (Actual); 2021-2040 (Extrapolated)



Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Figure 6 presents two non-linear specifications and the corresponding extrapolated data to parity. The more aggressive polynomial fit model assumes that the rate of growth continues to grow (faster growth each year) until parity, and forecasts parity in 2032. This second-order model accounts for the attention that 'Diversity, Equity, and Inclusion' (DEI) and gender initiatives have received only recently, despite the problem being widely reported for many decades (Dong 2021). While the polynomial model has a tight fit to historically observed values ($R^2 = 99.5\%$), the implicit assumption of continued exponential growth is dubious.

gender non-binary identifications that were not accessible for research in this study. See sections 8.9 and 8.10 for further discussion.

Previous work (Sandberg 2019) has argued that, among the candidates for executive positions, the cohort of women is richer in talent than the cohort of men because the latter has been relatively over-fished. Extending this argument, as the representation between genders approaches parity, the skill advantage for women should diminish. Furthermore, many firms have recognized the disproportionately low WRR and are embarking on corrective programs (Payscale 2021). A diminished emphasis on these programs, as WRR approaches parity, is a reasonable assumption. Therefore, a more conservative model would be a sigmoidal, or S-shaped, specification. Under such an assumption (Figure 6, dark blue), **$\boldsymbol{WRR}$ parity is expected in 2040.**

Despite the mathematical rigor of these models and their improvement over a linear assumption[10], this extrapolation to parity must be caveated. Small adjustments to the model assumptions and training data can have large effects on the results. Furthermore, these models are built on the WRR data, aggregated across all positions in table 1. Parity for specific positions that have seen slower progress, such as CEO, will likely take much longer.

5. Data

The **S&P Global Professionals** dataset was the source for executive data. The dataset includes board and company affiliations, executive biographies, standardized job functions, titles, education, and compensation for more than 4.5 million professionals going back to 1992.

Yewno Judicial Analytics dataset was the source for federal court case data. The dataset provides document level information from millions of court opinions with meta-tagging for legal themes, linking to global public entities, and the complete textual component of legal opinions.

The **S&P Global Alpha Factor Library (AFL)** dataset was the source for all firmographic data. AFL provides hundreds of pre-calculated factors including financial ratios, valuation metrics, price and momentum statistics, and analyst expectations. All factors are constructed using point-in-time data.

6. Conclusions

Equality among genders entails equal access to resources, opportunities, economic participation, and decision-making. Women do not have equal access to the same executive positions or the same compensation range for a given position as men. Compared to men, women in executive roles are more likely to receive compensation in a compressed range around the median of their peer group. This practice of Gender-Based Compensation Management (GBCM) artificially addresses the gender pay gap by increasing the median woman's compensation while still paying less to women as a group. Effectively, women have been given a glass floor as redress for the glass ceiling. Equitable conditions cannot arise from inequitable processes. Rather than aligning median compensation among women and

[10] See section 8.8 for expanded discussion.

men, inequitable processes must be corrected, and the success criterion should be an absence of institutional bias.

7. References

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8. Expanded Discussion and Robustness Checks

The research conclusions discussed in previous sections were derived from a robust methodology grounded in statistics, data science, and quantitative analysis. The detailed methodology is formally documented below. Section 8.1 discusses the benchmark methodology and framework for comparing pay ratio distributions; section 8.2 reviews the model validation protocol; sections 8.3, 8.4, and 8.5 provide robustness checks that show conclusions hold without adjustment by regression (in Z-score space), when removing possible token salaries, and accounting for attrition, respectively; section 8.6 provides an alternative framework that corroborates the findings in section 2; section 8.7 reviews the analysis of federal court defendants versus non-defendants; section 8.8 details the time-series modeling of the women's representation rate in senior roles; section 8.9 documents the approach to programmatically assign gender to the executives in our universe; section 8.10 discusses the choice of diction when referring to our labels ('gender' vs. 'sex').

8.1. Benchmarking Methodology and Formal Definitions

This section details the framework used to make compensation comparisons between women and men in executive roles, included in this work. For each year (2006-2020), executives holding one or more of the roles listed in table 2 for a firm that was a Russell 3000 constituent in the focal year were included in the analysis. Total calculated compensation (compensation type 18 in the CIQ Professionals dataset) attributed to a given calendar year for an included executive was summed for that year to obtain a total annual compensation value.

Table 2. Executive Professions Included in Analysis

	proFunctionId	profunctionname
Board Positions	47	Member of the Board of Directors
	45	Chairman of the Board
	43	Vice Chairman
	18	Secretary
	17	Treasurer
C-Suite	1	Chief Executive Officer
	6	Chief Financial Officer
	7	Chief Operating Officer
	12	Chief Accounting Officer
	15	Chief Technology Officer
	21	Chief Administrative Officer
	23	Chief Legal Officer
	77	Chief Scientific Officer
Senior Executives	8	Unit CEO
	9	Unit President
	22	Head of Investor Relations
	26	Head of Human Resources
	33	Finance and Accounting Professional
	36	Investment Professional
	37	Investor Relations Professional
	39	Operations Professional

Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

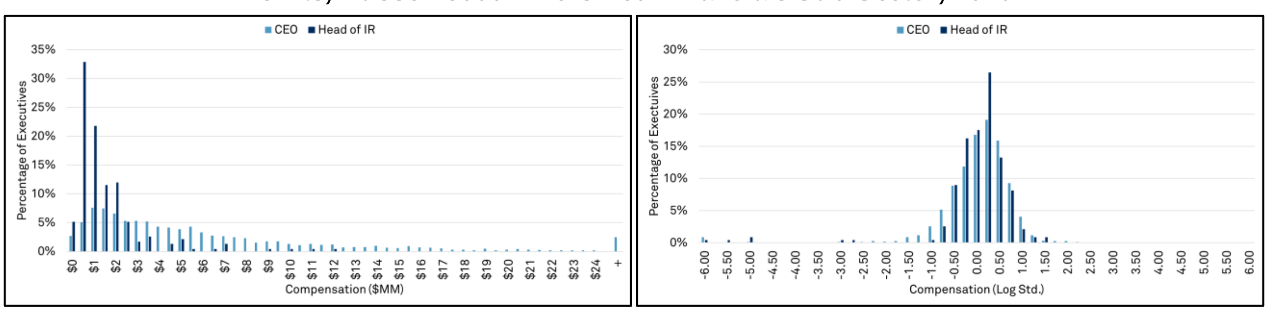
The main objective of this work is to draw statistically significant inferences about disparities between women and men in executive roles, which requires a framework for comparison. To properly attribute observed differences between women and men in the study to their gender, the framework must account for other variables that may otherwise explain such differences. Furthermore, the study of gender disparities at the executive level is mired in the small sample size dilemma. That is, the paucity of women in executive roles (one of the very problems commonly studied) is often a barrier in drawing statistically significant inferences from the corresponding data. The ideal framework, therefore, allows for study of all executives in aggregate instead of individually studying subsets of the data. Lastly, the framework for comparison should represent the observed differences between genders on an intuitive scale.

Compensation data for executives was natural log transformed to address right skew. The transformed values were standardized across each job function and sub-sector for a given year, to center all job / sub-sector subsets at zero with unity variance. Figure 7 shows the transform on two subsets of the data, compensation for CEO and Head of IR, brings the subsets onto a comparable scale.

$$Ln\_Comp_{it}^{job,SS,t} = \frac{Ln(comp_{it}) - ave^{job,SS,t}\{Ln(comp_{it})\}}{stdev^{job,SS,t}\{Ln(comp_{it})\}} \qquad \text{Eqn. 3}$$

Where $Ln\_Comp_{it}^{job,SS,t}$ is the log standardized compensation; subscripts imply a focal executive (i) at time (t); superscripts imply a function was calculated over the set of job functions in table 2 (job) and equity sub-sectors[11] (SS) at time t; ave and $stdev$ are the group average and standard deviation, respectively; Ln is the natural log function[12]; and $comp_{it}$ is the USD denominated total calculated compensation for executive (i) at time (t).

Figure 7: Distribution of CEO Compensation in $MM USD (Left) and Natural Log Standardized (Right) Units, Russell 3000 Diversified Financials Sub-Sector, 2020



Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

[11] Sub-sector refers to the Global Industry Classification Standard taxonomy at the 4-digit Industry Group level.
[12] The natural log function includes a shift of the data so the minimum compensation was $1.00. This was achieved by subtracting the minimum observed compensation and then adding $1.00, to all compensation values before taking the natural log.

Explanatory control variables in this study were used to estimate a benchmark compensation with a linear regression model,

$$Ln\_Comp_{it}^{job,SS,t} = \left[Ln\_Size_{it}^{SS,t} \quad Age_{it} \quad Tenure_{it} \quad is\_multiPos_{it} \quad 1\right] \circ \begin{bmatrix} \beta_{Size} \\ \beta_{Age} \\ \beta_{Tenure} \\ \beta_{is\_multiPos} \\ int \end{bmatrix}$$

Eqn. 4

Where $Ln\_Size_{it}^{SS,t}$ is the market capitalization of firm i at time t, after natural log standardization across sub-sector (SS),

$$Ln\_Size_{it}^{SS,t} = \frac{Ln(Size_{it}) - ave^{SS,t}\{Ln(Size_{it})\}}{stdev^{SS,t}\{Ln(Size_{it})\}}$$ Eqn. 5

Age_{it} and $Tenure_{it}$ are the age and number of years in the position for executive i at time t; $is\_multiPos_{it}$ is a categorical flag equal to 1 if executive i holds multiple positions with their employer at time t; β_x is the regression coefficient for regressor x; and int is the regression intercept.

Separate regressions were performed within job (job), sub-sector (SS), and time (t) subsets of the data. A given subset (sub) was included in the analysis if the number of executives was at least 30 and the number of women was at least 2, $|sub| \geq 30$ and $|sub_{woman}| \geq 2$. Otherwise, the set was excluded from analysis. Note that the benchmarking of compensation was done without adjusting for gender (gender effects were studied <u>after</u> the benchmark was determined). Therefore, subsets with less than 2 women, including subsets with 0 women, could be benchmarked and added to the analysis. These subsets would not likely change the analysis in a meaningful way because they would only add datapoints to the cohort of men (the baseline), and half the values in each subset are above (and half are below) the median of $1.00, by construction. Adding these subsets would increase the total number of datapoints without impacting the magnitude of gender comparisons and inflate the test statistics. While the inclusion of these subsets may be valid, the analysis as presented is more conservative. Restricting subsets further, such as requiring more women in a subset, is not necessary and may exclude meaningful datapoints in the cohort of women.

The regression equation was used to obtain in-sample predicted values for each executive's compensation within that subset. The best fit value for each executive's compensation in each year is represented by, $Ln\_\widehat{Comp}_{it}$. Predicted values were transformed back to a USD representation,

$$\widehat{comp}_{it} = exp^{\left(Ln\_\widehat{Comp}_{it} \circ stdev^{job,SS,t}\{Ln(comp)\}\right) + ave^{job,SS,t}\{Ln(comp)\}}$$ Eqn. 6

Where $\widehat{comp}$ represents the executive's benchmark salary accounting for the explanatory variables, denominated in USD; and exp represents the inverse natural log transform[13].

Each executive's true compensation is represented as a multiple of the executive's benchmark,

$$Unadjusted\_Pay\_Ratio_{it} = \frac{comp_{it}}{\widehat{comp}_{it}} \quad \text{Eqn. 7}$$

And for clarity of interpretation, the median pay ratio is set to $1.00,

$$Pay\_Ratio_{it} = \frac{Unadjusted\_Pay\_Ratio_{it}}{Median^{job,SS,t}(Unadjusted\_Pay\_Ratio_{it})} \quad \text{Eqn. 8}$$

Where $Median^{job,SS,t}$ represents the median $Unadjusted\_Pay\_Ratio$ within a job (job) and sub-sector (SS) subset of the data in a particular year (t).

Each executive's Pay_Ratio was bucketed into a discrete category, using the piecewise function,

$$Bin(Pay\_Ratio) = \begin{cases} \$0.70 & if\ Pay\_Ratio < \$0.70 \\ \$1.00 & if\ \$0.70 \leq Pay\_Ratio < \$1.30 \\ \$1.30 & if\ \$1.30 \leq Pay\_Ratio \end{cases} \quad \text{Eqn. 9}$$

Where numeric placeholders $0.70 represent the left-tail, $1.00 represents the middle, and $1.30 represents the right-tail.

Executives were then divided into groups by gender, women (W) and men (M). Generically, the employee density of a group at position x is given by,

$$G_{Distribution}(x) = \frac{\sum_G \begin{cases} 0 & if\ x \neq Bin(x) \\ 1 & if\ x = Bin(x) \end{cases}}{|G|} \quad \text{Eqn. 10}$$

$$x \in \{\$0.70, \$1.00, \$1.30\} \quad \text{Eqn. 10b}$$

Where $G_{Distribution}(x)$ is the percentage of employees in a given group that have a Pay_Ratio in bucket x; x indexes over our discrete buckets; the numerator of $G_{Distribution}(x)$ is a simple count of employees within the bucket; the denominator is a simple count of all employees in the group. For example, $Women_{Distribution}(\$1.00)$ is the percentage of all women that fall in the middle range of compensation ($\$0.70 \leq Pay\_Ratio < \$1.30$).

The difference in the percentage of employees between groups is given by,

[13] The inverse natural log function includes a shift of the data, such that exp^0 returns the minimum compensation for a given subset of the data. This was achieved by adding the minimum compensation and then subtracting $1.00, to all compensation values after taking the inverse natural log.

$$\Delta_{Men}^{Women} Distribution(x) = Women_{Distribution}(x) - Men_{Distribution}(x) \quad \text{Eqn. 11}$$

And a z-statistic for the difference between proportions is given by,

$$z_{Men}^{Women} = \frac{\Delta_{Men}^{Women} Distribution(x)}{SE_{Men}^{Women}(x)} \quad \text{Eqn. 12}$$

Where

$$SE_{Men}^{Women}(x) = \sqrt{p_{Men}^{Women}(1 - p_{Men}^{Women})\left(\frac{1}{|Men|} + \frac{1}{|Women|}\right)}$$

$$p_{Men}^{Women} = \frac{|Men| Men_{Distribution}(x) + |Women| Women_{Distribution}(x)}{|Men| + |Women|} \quad \text{Eqn. 12b}$$

8.2. Model Validation

Section 8.1 introduced the framework for comparison of executive compensation. This framework utilizes a regression model and the in-sample forecasts thereof. These forecasts are not observations, but they are treated as observations in the tests of statistical significance. A model validation step was performed to appropriately consider the model variance.

In place of using the best fit forecast from the regression model in eqn. 4, the regression forecast was modeled as a selection from a normal distribution,

$$\widehat{comp}_{it} = exp^{\left(\tilde{N}\left(Ln\_\widehat{Comp}_{it}, \sigma^2{}_{it}\right) \circ stdev^{job,SS,t}\{Ln(comp)\}\right) + ave^{job,SS,t}\{Ln(comp)\}} \quad \text{Eqn. 13}$$

Where $\widehat{comp}$ represents a probabilistically determined compensation for executive i at time t; the right side of eqn. 13 substitutes $\tilde{N}\left(Ln\_\widehat{Comp}_{it}, \sigma^2{}_{it}\right)$ for $Ln\_\widehat{Comp}_{it}$ in eqn. 6; $\tilde{N}\left(Ln\_\widehat{Comp}_{it}, \sigma^2{}_{it}\right)$ represents a value randomly selected with probability from a normal distribution (eqn. 13b) centered at $Ln\_\widehat{Comp}_{it}$ with variance $\sigma^2{}_{it}$

$$\tilde{N}\left(Ln\_\widehat{Comp}_{it}, \sigma^2{}_{it}\right) = \frac{1}{\sigma_{it}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - Ln\_\widehat{Comp}_{it}}{\sigma_{it}}\right)} \quad \text{Eqn. 13b}$$

Where the variance is determined from the regression equation for each datapoint,

$$\sigma^2{}_{it} = \left(\frac{\sum\left(Ln\_\widehat{Comp}_{it} - Ln\_Comp_{it}^{job,SS,t}\right)^2}{|G_{job,SS,t}| - 5}\right) \circ d_{it} \circ (D^T \circ D)^{-1} \circ d_{it}^T \quad \text{Eqn. 13c}$$

Where $|G_{job,SS,t}|$ is the number of datapoints in the regression, D is the regressor matrix for the explanatory variables, and d_{it} is the data vector for executive i at time t,

$$d_{it} = \left[Ln\_Size_{it}^{SS,t} \quad Age_{it} \quad Tenure_{it} \quad is\_multiPos_{it} \quad 1\right] \qquad \text{Eqn. 13d}$$

This process was repeated for each executive in the original analysis, until a complete new set of regression predictions was obtained probabilistically, using the model variance. The new regression predictions were used to generate pay ratios, discretized pay ratio bins, and evaluate the null hypothesis using the established equations. Each set of 3 p-values (for the lower ($0.70), middle ($1.00), and upper ($1.30) pay ratio range) represents a single Monte Carlo run. A total of 207,921 Monte Carlo simulations were run and results are summarized in table 3.

Table 3: Monte Carlo Range (n=207,921 simulations), Parameters Based on Executive Data in Russell 3000, 2020

	Diff	Diff %	P-Value	Women %	Men %
Left Tail (Pay Ratio <0.7)	Smallest	-3.6%	0.0%	22.9%	26.3%
	Average	-4.5%	0.0%	22.2%	26.7%
	Largest	-5.5%	0.0%	21.2%	26.7%
Mid Range (0.7 < Pay Ratio < 1.3)	Smallest	12.3%	0.0%	56.4%	44.2%
	Average	13.4%	0.0%	57.3%	44.0%
	Largest	14.6%	0.0%	58.2%	43.7%
Right Tail (Pay Ratio > 1.3)	Smallest	-7.8%	0.0%	21.5%	29.2%
	Average	-8.9%	0.0%	20.8%	29.7%
	Largest	-10.0%	0.0%	19.9%	29.9%

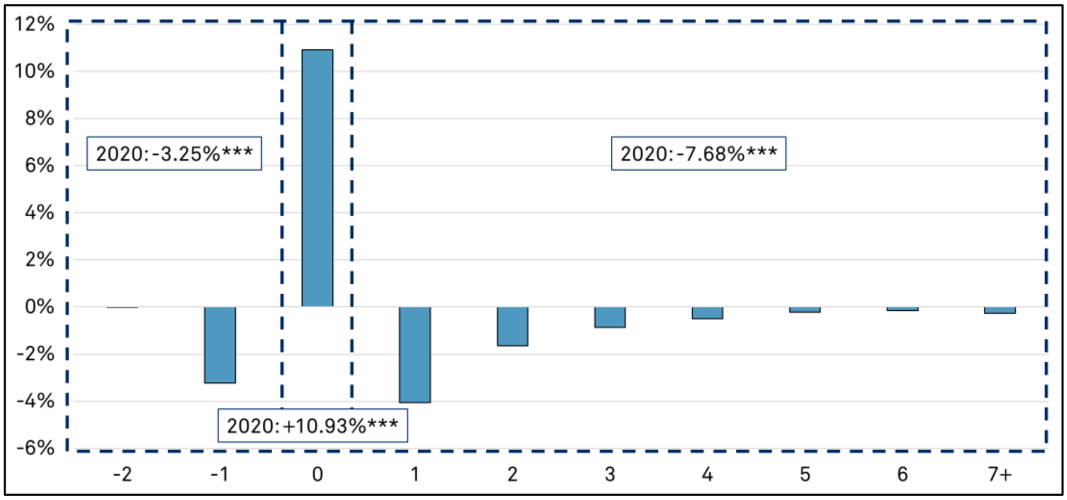
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

8.3. Evidence in Z-Scored Space

In lieu of the process outlined in section 8.1, the compensation of executives could be standardized (Z-scored) without performing any regression. While simpler, this approach is disadvantageous because it does not account for the effect of the explanatory variables included in the more rigorous treatment. Furthermore, the results are reported in Z-scored space, which lacks an intuitive interpretation. Nevertheless, the results in Z-scored space allow for a helpful comparison of the pre- and post-regression analysis. As a robustness check, these results are reported via figure 8.

Consistent with the more rigorous approach, the Z-scored approach shows women are more often compensated near the mean (Z-score ~ 0), compared to their male counterparts. Of the nearly 8,000 women in the study for year-end 2020, 88% were compensated within half of one standard deviation of the mean. This analysis shows that the GBCM effect is partially attenuated by the regression, instead of manifesting because of the regression. Therefore, the effect is not attributable to a positive confounding variable in the regression. A similar alternative framework is introduced as a robustness check in section 8.6.

Figure 8: Gender-Based Differences in Compensation is Z-score Space, Russell 3000 Executives, 2020



*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

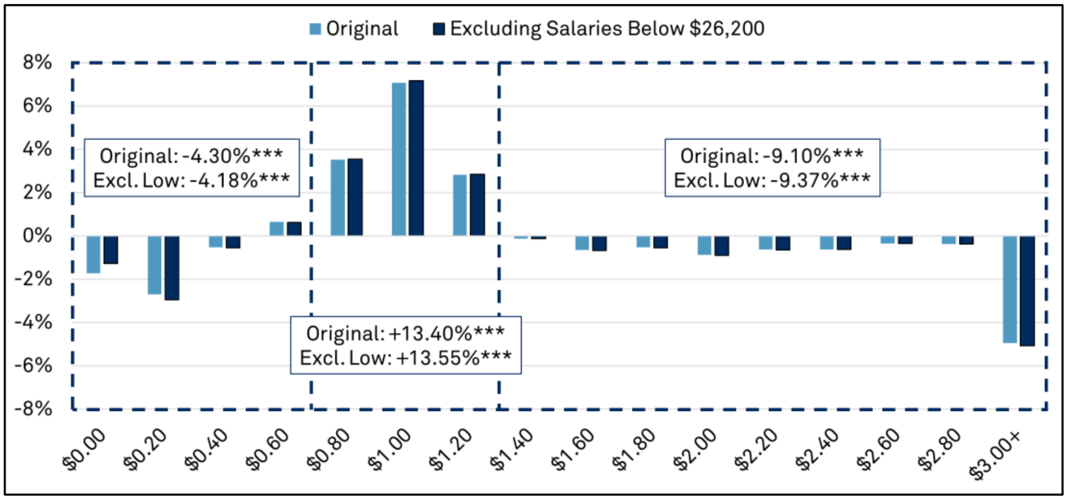
8.4. Token Salaries

A small subset of executives chose to forego market competitive salaries and instead opt for token salaries. These executives may receive their compensation in the form of stock options or grants. The analysis presented uses the total calculated compensation for an executive, which includes options and grants. However, some executives genuinely forego all compensation[14]. To ensure that the GBCM effect is <u>not</u> a manifestation of token salaries, the analysis was repeated after removing salaries below $26,200 USD[15]. As shown in figure 9, the GBCM effect is present in comparable if not larger magnitude after excluding salaries below $26,200.

[14] Gillet, R., Perino, M., 2019. “13 top executives who earn a $1 salary or less.” Business Insider, https://www.businessinsider.com/ceos-who-take-1-dollar-salary-or-less-2015-8

[15] The 2020 poverty line for a family of 4, including 2 children, is $26,200. Compensation above this value may not necessarily be market competitive, but certainly cannot be considered ‘token’ compensation. https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references/2020-poverty-guidelines

Figure 9: Gender-Based Differences in Compensation with and without token salaries, Russell 3000 Executives, 2020



*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

8.5. Attrition Among Women in Executive Roles

Figure 4 in section 2 shows that the underrepresentation of women in the tails of the compensation range (outside the middle) declined over the study period. The representation of women relative to men in the left tail (low range) declined from +0.17% in 2006 to -4.30% in 2020; and in the right tail from -6.75% in 2006 to -9.10% in 2020.

The explanation presented in section 2 is that firms are giving more (less) aggressive raises to women in the low (high) range relative to men, to push compensation towards the benchmark for women while subsidizing costs. A competing hypothesis is that women in the tails of the distribution are leaving their roles. Women's attrition could be from the workforce entirely or could be to firms outside the Russell 3000 universe. In either case, the attrition from the sample could be causing the reported GBCM effect.

To test the competing hypothesis, the attrition of men and women was evaluated in each section of the distribution (left tail, middle, and right tail) for each year in the study. Attrition was defined as the percentage of executives included in the analysis each year that were not in the analysis in the following year. Attrition only included individuals that left the sample. If an individual's company affiliation or job title changed, and the individual remained in the universe, the individual was not counted in the attrition total.

Table 4: Women's Attrition Relative to Men's Attrition from Russell 3000 Positions, Russell 3000 Executives, 2006-2019

Relative Attrition	Left Tail	Middle	Right Tail	All
12/31/2006	-4.83%***	-1.42%	-2.22%*	-2.72%***
12/31/2007	-0.31%	-2.29%**	-2.13%*	-2.02%***
12/31/2008	-2.47%**	-1.92%**	-3.17%**	-2.69%***
12/31/2009	0.43%	-3.18%***	-1.11%	-2.09%***
12/31/2010	-0.83%	-2.04%***	1.86%	-1.38%**
12/31/2011	-3.50%***	-4.04%***	-1.77%*	-3.76%***
12/31/2012	-1.88%*	-1.62%**	-0.66%	-1.89%***
12/31/2013	-3.41%***	-4.30%***	-2.18%**	-4.11%***
12/31/2014	-4.58%***	-4.46%***	-3.03%**	-4.49%***
12/31/2015	-4.51%***	-4.14%***	-2.12%*	-4.38%***
12/31/2016	-4.65%***	-3.06%***	-1.55%	-3.91%***
12/31/2017	-4.31%***	-4.07%***	-4.52%***	-4.80%***
12/31/2018	-4.92%***	-4.85%***	-3.18%***	-5.27%***
12/31/2019	-6.44%***	-5.46%***	-3.46%***	-5.88%***

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

In almost all years and all sections of the pay ratio distribution, the attrition was higher for men than for women. There were two exceptions: 1) attrition at the low end of the pay ratio was slightly higher, but not statistically significant, for women in 2009 during the great financial crisis (GFC); 2) attrition at the high end of the pay ratio was slightly higher, but not statistically significant, for women in 2010 during the initial post-GFC recovery. In both cases where attrition among women was higher, the difference was not statistically significant. The empirical evidence, therefore, supports the explanation presented in section 2, over the alternative hypothesis.

8.6. Regression with Gender as a Regressor

The framework introduced in section 2 and detailed in section 8.1 uses a regression equation to account for compensation differences attributable to several control variables, before examining differences attributable to gender. An alternative approach would be to include gender as a regressor in the presence of the control variables as covariates. The regression specification for this alternative model is given by eqn. 14.,

$$Ln\_Comp_{it}^{job,SS,t} = \begin{bmatrix} Ln\_Size_{it}^{SS,t} & Age_{it} & Tenure_{it} & is\_multiPos_{it} & is\_Woman_i & 1 \end{bmatrix} \circ \begin{bmatrix} \beta_{Size} \\ \beta_{Age} \\ \beta_{Tenure} \\ \beta_{is\_multiPos} \\ \beta_{is\_Woman} \\ int \end{bmatrix}$$

Eqn. 14

Where all variables have been previously defined except is_Woman_i, a categorical variable equal to 0 for men and 1 for women.

Table 5: Regression Coefficients for Gender, Russell 3000 Executives, 2006-2020, Full Sample and Sample Divided at the Median

Coefficients (T-Stat)	is_Female (Full Sample)	is_Female (Below Log Mean)	is_Female (Above Log Mean)
2006	-0.10*** (-6.61)	+0.06*** (2.85)	-0.15*** (-8.97)
2007	-0.12*** (-8.55)	+0.04** (2.15)	-0.17*** (-9.51)
2008	-0.11*** (-7.50)	+0.05*** (3.26)	-0.15*** (-7.92)
2009	-0.09*** (-6.00)	+0.06*** (2.76)	-0.12*** (-10.11)
2010	-0.02 (-1.60)	+0.15*** (6.41)	-0.11*** (-9.72)
2011	-0.03** (-1.98)	+0.15*** (6.00)	-0.12*** (-11.49)
2012	-0.03** (-2.01)	+0.16*** (6.67)	-0.12*** (-11.82)
2013	-0.02 (-1.55)	+0.17*** (7.09)	-0.10*** (-10.43)
2014	-0.01 (-1.09)	+0.18*** (7.93)	-0.11*** (-10.96)
2015	0.00 (0.10)	+0.20*** (8.54)	-0.10*** (-10.97)
2016	-0.03** (-2.05)	+0.15*** (6.94)	-0.11*** (-11.38)
2017	-0.04*** (-3.12)	+0.15*** (7.27)	-0.12*** (-12.52)
2018	-0.04*** (-3.35)	+0.11*** (6.02)	-0.12*** (-12.35)
2019	-0.06*** (-5.28)	+0.07*** (4.39)	-0.13*** (-11.98)
2020	-0.05*** (-4.25)	+0.09*** (5.60)	-0.14*** (-13.63)

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Unlike the regression outlined in section 8.1, where the objective was to obtain best linear estimates of compensation given the control variables, the objective with this specification is to examine the regression coefficient on the is_Woman regressor. Consequently, whereas the number of women in the training data for the regression presented in eqn. 4 is irrelevant[16], the number of women in this specification must be large to obtain reasonable results. For this reason, the entire set of compensation observations for each year (t), from 2006-2020, was regressed to obtain a single set of regression coefficients per year. Compared to the separate

[16] The regression in section 8.1 does not include gender as a regressor. Each executive's benchmark is determined without any consideration for the executive's gender and therefore, the benchmark training data need not include women in the set. See discussion in section 8.1 for more details.

regressions for each year (t), job (job), and sub-sector (SS) that were used in section 8.1, this approach includes more women in the training data at the cost of less flexibility in the regression coefficients. Note that the standardization protocol (eqn. 3) remains the same. That is, the standardization of the natural log of compensation was relative to a particular year (t), job (job), and sub-sector (SS). To address potential collinearity between covariates, a generalize least squares approach was used.

Because the regression was performed in log standardized space, the magnitude of the coefficients lacks an intuitive meaning. Instead, the interpretation of results relies on the sign and the statistical significance on the is_Woman regressor. Specifically, 1) a negative (positive) coefficient implies women are compensated below (above) men and 2) the statistical significance indicates the relationship strength relative to the noise in the training data, where relationships with p-values below the 95% confidence level are typically regarded as subsumed by noise.

The regression coefficients range from a not significant 0.00 to a highly significant -0.12 (table 5), with no obvious trend over time. The most recent value (2020) was mid-range at -0.05. The inconsistency of the coefficient's sign and magnitude, with no clear trend over time, suggests that the relationship between compensation and gender is not well explained by a single linear model.

The regression analysis was repeated after dividing the dataset in half at the mean of the dependent variable. All regression coefficients for the half below (above) the middle were statistically significant and positive (negative), indicating a compensation advantage (disadvantage) for women earning compensation below (above) their peers. Covariate information for the full regression is reported in table 6. Comparable coefficients for the covariates were obtained for the sub-sample regressions divided at the log mean value (not shown).

The key takeaway from this analysis is a corroboration of the results presented in the main paper using a different framework. Specifically, among executives compensated (above) below the middle, women have a compensation (dis-)advantage and earn (less) more than their male peers.

Table 6. Linear Model Regression Coefficients, Russell 3000, 2006-2020

Coefficients (T-Stat)	R2	is_Woman	Size	Age	Tenure	Multiple Positions	Int
2006	0.19	-0.10*** (-6.61)	0.3*** (70.91)	-0.04*** (-8.85)	0.10*** (21.96)	0.57*** (62.51)	-0.28*** (-44.03)
2007	0.16	-0.12*** (-8.55)	0.26*** (64.85)	-0.05*** (-9.99)	0.09*** (20.95)	0.52*** (60.80)	-0.23*** (-39.72)
2008	0.15	-0.11*** (-7.50)	0.24*** (60.78)	-0.04*** (-9.15)	0.08*** (17.92)	0.53*** (61.15)	-0.23*** (-39.63)
2009	0.14	-0.09*** (-6.00)	0.28*** (66.96)	-0.02*** (-5.04)	0.08*** (16.55)	0.47*** (52.67)	-0.21*** (-35.23)
2010	0.13	-0.02 (-1.60)	0.28*** (66.25)	-0.02*** (-3.39)	0.07*** (13.88)	0.45*** (49.58)	-0.21*** (33.92)
2011	0.12	-0.03** (-1.98)	0.26*** (60.96)	0.00 (0.24)	0.07*** (14.72)	0.45*** (49.27)	-0.21*** (-33.60)
2012	0.12	-0.03** (-2.01)	0.26*** (61.87)	0.00 (0.13)	0.06*** (13.36)	0.44*** (48.96)	-0.21*** (-33.40)
2013	0.11	-0.02 (-1.55)	0.25*** (58.79)	0.01 (1.93)	0.06*** (13.32)	0.43*** (47.49)	-0.20*** (-32.61)
2014	0.12	-0.01 (-1.09)	0.25*** (57.60)	0.01 (1.05)	0.06*** (11.73)	0.46*** (50.29)	-0.21*** (-33.74)
2015	0.11	0.00 (0.10)	0.24*** (54.72)	0.01** (2.22)	0.05*** (11.28)	0.44*** (47.23)	-0.20*** (-31.75)
2016	0.13	-0.03** (-2.05)	0.27*** (61.83)	0.00 (0.08)	0.05*** (10.38)	0.46*** (49.66)	-0.21*** (-33.09)
2017	0.13	-0.04*** (-3.12)	0.27*** (62.75)	0.00 (0.70)	0.05*** (9.46)	0.45*** (48.46)	-0.20*** (-31.78)
2018	0.13	-0.04*** (-3.35)	0.27*** (61.23)	-0.01 (-1.80)	0.04*** (8.90)	0.45*** (48.31)	-0.19*** (-30.76)
2019	0.14	-0.06*** (-5.28)	0.27*** (62.67)	-0.03*** (-5.23)	0.04*** (8.37)	0.46*** (50.30)	-0.19*** (-30.74)
2020	0.13	-0.05*** (-4.25)	0.27*** (61.28)	-0.03*** (-5.85)	0.03*** (7.11)	0.45*** (48.44)	-0.19*** (-29.42)

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

8.7. Is GBCM Poor Governance? – Extended Discussion

Federal court opinions related to select compensation or governance themes (Table 7) were obtained from the Yewno Judicial Analytics dataset. The detailed methodology for comparing women's compensation to men's compensation can be found in section 8.1. That methodology was separately applied for defendant firms and non-defendant firms. To evaluate the difference between defendant (D) and non-defendant (ND) firms in the differences between compensation for women and men (difference of differences),

$$\Delta_{ND}^{D} Distribution(x) = \{\Delta_{Men}^{Women} Distribution(x)\}_D - \{\Delta_{Men}^{Women} Distribution(x)\}_{ND}$$

Eqn. 15

Where $\Delta_{Men}^{Women} Distribution(x)$ is defined in equation 11 and $\{\Delta_{Men}^{Women} Distribution(x)\}_G$ is the equivalent quantity calculated only over the set of executives employed by firms in group G, and G is either defendant (D) or non-defendant (ND).

Table 7: Judicial Themes (Top) and Distinct Company and Executive Counts (Bottom) for Selected Federal Court Cases

	judicialThemeId	judicialThemeName
Compensation	4	billing, costs, & wages
	8	contract work
	9	contracts & payments
	13	earnings & income
	15	employee disability, injury, & compensation
Governance	12	disciplinary actions
	38	work place affairs
	16	employer discrimination
	6	committees & governance
	21	fraud

Year	Defendant Firms	Executives at Defendant Firms	Non-Defendant Firms	Executives at Non-Defendant Firms
2008	291	4,247	2,593	39,971
2009	311	4,507	2,617	40,971
2010	297	4,301	2,604	40,599
2011	265	3,796	2,637	40,194
2012	192	2,877	2,734	40,668
2013	196	2,748	2,774	41,057
2014	199	2,888	2,794	41,777
2015	219	3,160	2,727	40,122
2016	201	2,967	2,699	40,640
2017	207	2,994	2,683	40,078
2018	216	3,111	2,721	40,461
2019	165	2,401	2,755	40,168
2020	175	2,484	2,802	40,553

Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

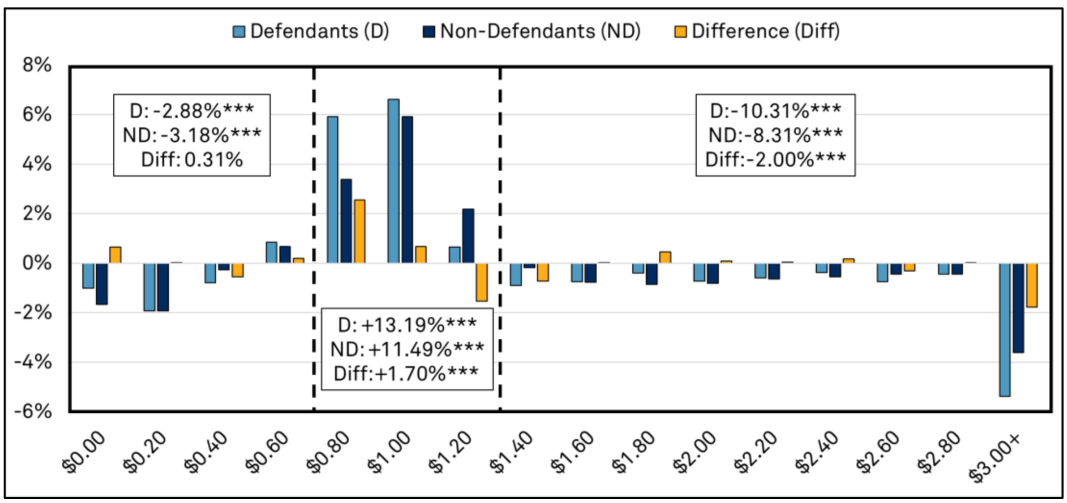
The statistical significance of the difference of differences was obtained from extending the Z-test of proportions (defined in eqn. 12),

$$z_{ND}^{D} = \frac{\Delta_{ND}^{D} Distribution(x)}{\sqrt{\{SE_{Men}^{Women}(x)\}_D^2 + \{SE_{Men}^{Women}(x)\}_{ND}^2}} \qquad \text{Eqn. 16}$$

Where $SE_{Men}^{Women}(x)$ is defined in eqn. 12b and $\{SE_{Men}^{Women}(x)\}_G$ is the equivalent quantity calculated only over the set of executives employed by firms in group G, and G is either defendant (D) or non-defendant (ND).

The analysis in section 3 covers GBCM differences between defendant and non-defendant firms in 2020 only and comes with a caveat on small sample size. The total number of executives at defendant firms was 2,484 (table 7), of which 577 were women. When bucketing the compensation for these 577 women, the right tail ($pay\ ratio > \$1.30$) contains only 84 observations and the left tail ($pay\ ratio < \$0.70$) contains only 101 observations. A larger sample size could be obtained by creating defendant and non-defendant groups in each year, from 2008-2020, and combining compensation for executives in each group over time. The resulting set includes 42,481 executives employed by defendant firms, of which 6,533 are women with over 1,100 in each tail. The larger sample analysis, shown in figure 10, was consistent with the results presented in section 3. The approach of combining multiple years of data implicitly makes a liberal assumption of independence in pay ratio distribution between years. For this reason, the more conservative analysis performed on data from 2020 only was included in section 3. This analysis is offered with caveat for additional consideration.

Figure 10: Pay Ratio Distribution Differences between Defendants in Select Federal Court Cases and Non-Defendants, Russell 3000 Firms, 2006-2020



*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level
Source: S&P Global Market Intelligence Quantamental Research. Data as of August 26, 2021.

Section 3 implies an association between GBCM and poor governance. Governance-related federal court cases that have reached a decision (i.e., not settled out of court nor awaiting decision) were used as the empirical proxy for poor governance. The premise axiomatically asserts that firms that have been defendants have, on average, poor governance in comparison to those firms that have not been defendants in the same year. The research did not produce conclusive findings on the casual relationship between GBCM and legal disputes. GBCM may create feelings of inequity that lead to legal disputes. Alternatively, legal disputes may encourage defendant firms to apply compensation benchmarks more stringently, leading to more pronounced GBCM. The causal effect is difficult to disentangle due to the increase in GBCM characteristics for all firms over the study period and remains a topic for future study.

8.8. Time-Series Models of Women's Representation in Senior Positions

Section 4 presents two time-series models of WRR extracted to parity. Each model was trained on the observed WRR from 2010-2020.

Over the last decade, WRR growth rates have increased from 0.3% in 2011 to 1.7% in 2020. The consistent year-over-year increase (positive first derivative) in WRR, coupled with the increased growth rate (positive second derivative) bode well for a trend towards reaching parity. Because WRR growth has been small ($< 2\%$) and the rate of progress changes from year-to-year, establishing a realistic data-driven estimate for when women will have parity has proven a challenging task.

Non-linear models were selected because the growth rate of WRR increases over the study period, indicating a positive second derivative for WRR. Linear models fail to provide accurate forecasts and are sensitive to new data for systems with positive slope and convexity. For example, a linear extrapolation on WRR in 2010, 2014, and 2020 would estimate parity in 2135 (125 years), 2088 (74 years), and 2055 (35 years), respectively. Each reparameterization of the model attempts to capture the larger growth rate of WRR, but assumes no additional increase in the growth rate of WRR in the extrapolation period.

The second-order polynomial captures the increasing growth rate of WRR over the training period, but assumes the growth rate increases at the same pace as it increased during the training period. Under this assumption and extrapolating beyond parity, all executive positions will be held by women in 2042, which is an unlikely outcome.

The sigmoidal model assumes the second derivative moves in a pendulum fashion. Specifically, the second derivative will reach a maximum, retracing a path to 0, and turn negative at the so-called inflection point. When constructing a sigmoidal time-series model without observing the inflection point, an inflection point must be assumed. In this work, the inflection point was assumed in 2025.

8.9. Gender Assignments

Gender assignments for each executive were determined by the following methodology.

1. The executives' honorifics were queried from the S&P Global Professionals Dataset. The following gender assignments were made on honorifics.
    a. The label, 'woman', was assigned to executives with the honorifics: Baroness, Countess, First Lady, Lady, Madam, Miss, Mrs., Ms., or Sister.
    b. The label, 'man', was assigned to executives with the honorifics: Bishop, Count, Father, Hafiz, Janab, Lord, Mian, Mr., Sheikh, Sir.
    c. The label, 'ambiguous', was assigned to all other honorifics, such as Lieutenant, Doctor, Attorney, and more than 60 others.

2. A biography for each executive was queried from the S&P Global Professionals Dataset. Biographies were parsed by white space to identify individual words.
    a. The label, 'woman', was assigned to biographies containing female pronouns ('she', 'her', 'hers').
    b. The label, 'man', was assigned to biographies containing male pronouns ('he', 'him', 'his').
    c. The label, 'ambiguous', was assigned to biographies not containing any gender pronouns or containing both male and female pronouns.

3. In cases where both methods yielded unambiguous assignments in agreement or one method was ambiguous, the unambiguous gender assignment was used. In cases where the two methods yielded unambiguous assignments in disagreement or both methods yielded ambiguous assignments, the ambiguous gender assignment was used.

After implementation, the final dataset used for analysis contained 81,849 distinct male executives (men), 11,731 distinct female executives (women), and 322 ambiguous assignments. Records associated with the 322 ambiguous executives (0.34%) were omitted from additional analysis.

8.10. Diction: Gender vs. Sex[17]

We would be remiss to publish an article on gender without a brief discussion on the modern vernacular. Historically, "gender" and "sex" were interchangeable terms that referred to the set of two identities: male and female. Today, the terminology has evolved such that "sex" refers to chromosomal (XX versus XY) identity; whereas gender refers to social and cultural identities that extend beyond male and female. Conflating the two terms can be misconstrued as dismissive of gender-nonconforming identities and, therefore, the choice of diction is explained below.

In this work, we apply "male" and "female" labels[18] to company executives. The use of these binary assignments would favor using the term "sex". However, the use of the executives' preferred pronouns and honorifics in making the assignments would favor using the term "gender". A deeper examination of the topic,[19] has revealed a single precedent within our study in which an executive was male by sex and female by gender: Martine Rothblatt, CEO of United Therapeutics. In this case, our approach to gender assignment labeled Dr. Rothblatt as female. This precedent was used as a tie-breaker and, consequently, the term "gender"

[17] Parts of section 8.10. '*Diction: Gender vs. Sex*', were copied verbatim or paraphrased from our earlier research. See Sandberg, D.J., 2019. "#ChangePays: There *Were* More Male CEOs Named John, than Female CEOs." S&P Global Quantamental Research. https://www.spglobal.com/marketintelligence/en/news-insights/research/changepays-there-were-more-male-ceos-named-john-than-female-ceos
[18] The label "female" ("male") includes synonyms such as "woman" ("man") or "women" ("men").
[19] Kerrigan, S., 2018. "27 Most Successful LGBT+ Entrepreneurs, Executives, and Opinion Leaders." Interesting Engineering. https://interestingengineering.com/27-most-successful-lgbt-entrepreneurs-executives-and-opinion-leaders

was used throughout. We underscore the thought and analysis that went into this decision and emphasize no intention to dismiss non-binary gender identities.

Our Recent Research

September 2021: The Board Matrix: The (ESG) Value of Well-Connected Directors

Corporate boards are responsible for shaping and overseeing environmental, social and governance (ESG) policies for their organizations. This report examines the relationship between companies connected through shared board members and ESG performance. It finds that companies with strong board networks (companies with directors who serve on more than one corporate board or are well-connected) have better certain ESG outcomes than firms with weak board networks. Well-connected directors can utilize their network for information on emerging ESG trends/best practices and share this knowledge with their companies. Given their roles on multiple boards, well-connected directors are also better informed about the needs of different stakeholders (governments, communities, ESG activists) than directors with little or no network. This awareness of stakeholder management translates to better ESG performance for companies with well-connected directors.

August 2021: Technology Momentum: Peer Networks from Patents

Companies with similar patent portfolios exhibit peer group momentum. A strategy that buys (sells) stocks of focal companies in the Russell 3000 with outperforming (underperforming) technology peers produces an annualized risk-adjusted return of 5.23% in a historical backtest. The strategy returns are more pronounced for smaller companies. In the Russell 2000, the strategy demonstrates more efficacy with annualized long-short return of 7.32%. The strategy is distinct from sector momentum strategies. After controlling for sector momentum, 3.60% excess return in the Russell 3000 can be attributed to technology peer group momentum.

July 2021: Branching Out: Graph Theory Fundamentals

Investment analysis has evolved beyond financial data to non-financial, or alternative data. Typically, the focus has been on using alternative datasets that are purely time-series and tabular. Graph networks meanwhile offer investors the ability to gain deeper insights into the connections between economies, industries, and individual corporations.

May 2021: U.S Filings: No News is Good News

Company annual filings are a vital but often under-analyzed source of information for investors. Market moving content is buried within an ever-growing body of text that on average is equivalent to a 240-page novel. The filings contain subtle revisions making a computational linguistic approach imperative. Faced with this voluminous amount of text and the minute number of changes, investors have historically overlooked the newly embedded information and the implications of those additions

March 2021: Hiding in Plain Sight – Risks That Are Overlooked

This report uses three metrics (Minimum Edit Distance, Jaccard Similarity, and Cosine Similarity) to identify companies that made significant changes to the "Risk Factors" section of their filings. These metrics can serve as alpha signals or be used to quickly identify a pool of companies that require further investigation.

January 2021: **Leadership Change That Matters: A Value and Momentum Story**
December 2020: **Warranted Optimism: Sentiment vs. Supply Chain**
December 2020: **A Dark Winter for REITS: Trouble Brewing**
October 2020: **Sweet Spots in the C-Suite: Executive Best Practices for Shareholder Friendly Firms**

October 2020: **Just the (Build)Fax: Property Intelligence from Building Permit Data**
August 2020: **The Analyst Matrix: Profiting from Sell-Side Analysts' Coverage Networks**
June 2020: **The Information Supply Chain Begins Recovering From COVID**
May 2020: **Never Waste a Crisis: Following the Smart Money Through Beneficial Ownership Filings**
May 2020: **Risky Business: Foot Traffic, Vacancy Rates and Credit Risks**
May 2020: **Finding the Healthy Stocks in Health Care During Lockdown**
May 2020: **No More Walks in the (Office) Park: Tying Foot Traffic Data to REITs**
May 2020: **Do Markets Yearn for the Dog Days of Summer: COVID, Climate and Consternation**
April 2020: **Cold Turkey - Navigating Guidance Withdrawal Using Supply Chain Data**
April 2020: **Data North Star - Navigating Through Information Darkness**
March 2020: **Long Road to Recovery: Coronavirus Lessons from Supply Chain and Financial Data**
February 2020: **Ship to Shore: Mapping the Global Supply Chain with Panjiva Shipping Data in Xpressfeed™**
January 2020: **Natural Language Processing – Part III: Feature Engineering Applying NLP Using Domain Knowledge to Capture Alpha from Transcripts**
December 2019: **The "Trucost" of Climate Investing: Managing Climate Risks in Equity Portfolios**
October 2019: **#ChangePays: There Were More Male CEOs Named John than Female CEOs**
June 2019: **Looking Beyond Dividend Yield: Finding Value in Cash Distribution Strategies**
June 2019: **The Dating Game: Decrypting the Signals in Earnings Report Dates**
May 2019: **Bridges for Sale: Finding Value in Sell-Side Estimates, Recommendations, and Target Prices**
February 2019: **U.S Stock Selection Model Performance Review**
February 2019: **International Small Cap Investing: Unlocking Alpha Opportunities in an Underutilized Asset Class**
January 2019: **Value and Momentum: Everywhere, But Not All the Time**
November 2018: **Forging Stronger Links: Using Supply Chain Data in the Investing Process**

September 2018: Their Sentiment Exactly: Sentiment Signal Diversity Creates Alpha Opportunity

September 2018: Natural Language Processing – Part II: Stock Selection: Alpha Unscripted: The Message within the Message in Earnings Calls

July 2018: A Case of 'Wag the Dog'? - ETFs and Stock-Level Liquidity

June 2018: The (Gross Profitability) Trend is Your Friend

May 2018: Buying the Dip: Did Your Portfolio Holding Go on Sale?

March 2018: In the Money: What Really Motivates Executive Performance?

February 2018: The Art of the (no) Deal: Identifying the Drivers of Canceled M&A Deals

January 2018: U.S Stock Selection Model Performance Review

September 2017: Natural Language Processing - Part I: Primer

July 2017: Natural Language Processing Literature Survey

June 2017: Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment

April 2017: Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data

March 2017: Capital Market Implications of Spinoffs

January 2017: U.S. Stock Selection Model Performance Review 2016

November 2016: Electrify Stock Returns in U.S. Utilities

October 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 2

September 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 1

August 2016: Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)

July 2016: Preparing for a Slide in Oil Prices -- History May Be Your Guide

June 2016: Social Media and Stock Returns: Is There Value in Cyberspace?

April 2016: An IQ Test for the "Smart Money" – Is the Reputation of Institutional Investors Warranted?

March 2016: Stock-Level Liquidity – Alpha or Risk? - Stocks with Rising Liquidity Outperform Globally

February 2016: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2015

January 2016: What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News

November 2015: Late to File - The Costs of Delayed 10-Q and 10-K Company Filings

October 2015: Global Country Allocation Strategies

September 2015: Research Brief: Building Smart Beta Portfolios

September 2015: Research Brief – Airline Industry Factors

August 2015: Point-In-Time vs. Lagged Fundamentals – This time i(t')s different?

August 2015: Introducing S&P Capital IQ Stock Selection Model for the Japanese Market

July 2015: Research Brief – Liquidity Fragility

May 2015: Investing in a World with Increasing Investor Activism

April 2015: Drilling for Alpha in the Oil and Gas Industry – Insights from Industry Specific Data & Company Financials

February 2015: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2014

January 2015: Research Brief: Global Pension Plans - Are Fully Funded Plans a Relic of the Past?

January 2015: Profitability: Growth-Like Strategy, Value-Like Returns - Profiting from Companies with Large Economic Moats

October 2014: Lenders Lead, Owners Follow - The Relationship between Credit Indicators and Equity Returns

July 2014: Factor Insight: Reducing the Downside of a Trend Following Strategy

May 2014: Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model

April 2014: Riding the Coattails of Activist Investors Yields Short and Long Term Outperformance

March 2014: Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources

February 2014: Obtaining an Edge in Emerging Markets

February 2014: U.S Stock Selection Model Performance Review

January 2014: Buying Outperformance: Do share repurchase announcements lead to higher returns?

October 2013: Informative Insider Trading - The Hidden Profits in Corporate Insider Filings

September 2013: Beggar Thy Neighbor – Research Brief: Exploring Pension Plans

August 2013: Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets: The Foundations of Outperformance

July 2013: Inspirational Papers on Innovative Topics: Asset Allocation, Insider Trading & Event Studies

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April 2013: Complicated Firms Made Easy - Using Industry Pure-Plays to Forecast Conglomerate Returns.

March 2013: Risk Models That Work When You Need Them - Short Term Risk Model Enhancements

March 2013: Follow the Smart Money - Riding the Coattails of Activist Investors

February 2013: Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012

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December 2012: Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover

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September 2012: **Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?**
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January 2012: **S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011**
January 2012: **Intelligent Estimates – A Superior Model of Earnings Surprise**
December 2011: **Factor Insight – Residual Reversal**
November 2011: **Research Brief: Return Correlation and Dispersion – All or Nothing**
October 2011: **The Banking Industry**
September 2011: **Methods in Dynamic Weighting**
September 2011: **Research Brief: Return Correlation and Dispersion**
July 2011: **Research Brief - A Topical Digest of Investment Strategy Insights**
June 2011: **A Retail Industry Strategy: Does Industry Specific Data tell a different story?**
May 2011: **Introducing S&P Capital IQ's Global Fundamental Equity Risk Models**
May 2011: **Topical Papers That Caught Our Interest**
April 2011: **Can Dividend Policy Changes Yield Alpha?**
April 2011: **CQA Spring 2011 Conference Notes**
March 2011: **How Much Alpha is in Preliminary Data?**
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January 2011: **US Stock Selection Models Introduction**
January 2011: **Variations on Minimum Variance**
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