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Impact-Weighted Accounts Project Research Report

Abstract

Using new data on workforce composition and wages, we systematically measure the employment impact at U.S. firms from 2008 to 2020, including 2,682 unique firms and 22,322 firm-year observations. We document significant variation across industries and firms within each industry suggesting substantial heterogeneity of firm human capital strategies. Employment impact is moderately associated with lower employee turnover and higher firm valuation, while firms that have higher sales and invest more in innovation exhibit higher employment impact. Our results collectively demonstrate the feasibility and value of employment impact accounting.

Keywords: human capital, impact accounting, ESG, employee turnover, diversity

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1. Introduction

Organizational employment practices are of great importance to local labor markets and the socio-economic outcomes of workers and their families (Tait et al. 1989; Bowling 2010; Rothwell and Crabtree 2019). Firms produce significant positive and negative impacts through their workforce-related decisions, whether that means raising wages to meet minimum subsistence standards (such as at L'Oreal and Unilever), increasing hiring of Black employees to narrow the racial wealth gap (such as at Bank of America and IBM), or guaranteeing paid sick leave to employees to curb the spread of COVID-19 (such as at Ford Motors and Verizon) (Sustainable Trade Initiative 2021; OneTen 2020; JUST Capital 2021). However, despite the intrinsic and universal importance of labor practices to individual and societal wellbeing, information regarding corporate policies related to labor remains highly variable by firm, industry, and geography.

As a result, there is a growing call to increase the standardization and rigor of employment impact measurement, as well as significant progress in consensus-building across standard setters and reporting bodies.[1] Further, momentum is building around efforts to integrate impact reporting within financial statements, as evidenced by the work of the IFRS International Sustainability Standards Boards. The rationale and opportunity for impact accounting is taking a more central role in the dialogue regarding corporate performance and reporting (Serafeim et al. 2019; Rouen and Serafeim 2021; Nicholls and Zochowski 2020; Barker et al. 2020).

We build on the momentum from the rising emphasis on the "S" in ESG, as well as the magnification of employment-related issues during the COVID-19 pandemic, to present a large-scale analysis of employment impact at U.S. firms from 2008 to 2020, including 2,682 unique firms and 22,322 firm-year observations. The primary goal of this paper is to demonstrate the

[1] See, for example, the 2020 announcement on the merging of Sustainability Accounting Standards Board and the International Integrated Reporting Council to create the Value Reporting Foundation, as well as the statement from five major standard setters to increase cooperation and streamlining of efforts.

feasibility and value of large-scale analysis of employment impact. This paper builds upon the framework established in Freiberg, Panella, Serafeim, and Zochowski (2020) to measure and compare the impact of employment practices across organizations.

The impact dimensions analyzed in this paper are rooted in the work of a wide range of scholars and organizations who have studied labor market dynamics and employment practices long before the launch of the Impact-Weighted Accounts Initiative. In Appendix 1 we present a mapping of the IWA employment impact dimensions with a selection of other efforts. While this is not exhaustive, it represents the potential feasibility of creating impact-weighted employment accounts based on a range of existing metrics. In this way, we propose a monetization methodology for employment impact that is both flexible in terms of its inputs (metrics), as well as standardized in its outputs (monetized impact figures).

Measurement of employment impact across a large sample of U.S. firms allows us to examine how impact and its components are associated with two relevant firm characteristics: accounting performance and employee turnover. To conduct this large-scale analysis, we narrow our focus to the employment impact dimensions for which sufficient data are available: wage quality, opportunity, diversity, and location.[2] The importance of each dimension to the impact of firm employment practices on labor market inequalities and the measurement design is explained below. For further detail regarding the rationale for each impact dimension, see Freiberg et al. (2020).

The quality of wages is a widely accepted determinant of levels of wellbeing and inequality around the world (Bravemen and Gottlieb 2014; Vionnet and Haut 2018). The *wage quality* dimension of this paper considers the degree to which organizations' wage practices meet living

[2] Our estimates do not take into account the wage equity, career advancement, and health and well-being impact dimensions in Freiberg et al. (2020).

wage standards and are within reasonable bounds given local income satiation levels. The monetization method for *wage quality* thereby incentivizes firms to pay salaries that are at least equivalent to the living wage and to focus on wages paid to mid-and low-level employees that are historically disenfranchised from the gains of economic growth.

Significant barriers to employment and resulting skewed representation of demographic groups within an organization also contribute to disparities in labor market outcomes (Penner 2008; Grodsky and Pager 2001; Cajner et al. 2017). The *diversity* dimension measures how closely a company's gender and racial demographics reflect the demographics of the local population. The *opportunity* dimension evaluates how closely a company's hierarchy and representation across different job roles reflect the demographics of the company as a whole by examining seniorities and job categories within the firm. Together, these measurements push companies toward equitable recruitment, hiring, and internal mobility practices by rewarding companies for less underrepresentation of demographic groups across the total workforce and each workforce level.

Lastly, a large driver of socioeconomic inequalities is the inequitable access to decent work across geographies (ILO 2020; Gibb et al. 2014). The *location* dimension captures a firm's contribution to local employment opportunities. This metric incentivizes firms to create employment opportunities in geographical areas with high unemployment where jobs are most needed.

These four impact dimensions (wage quality, diversity, opportunity, and location) are combined to calculate a measure of *employment impact intensity* for each firm, which is defined as total employment impact scaled by the number of employees. *Employment impact intensity* can be interpreted as "impact per employee".

The primary data source for our firm-level employment data is Revelio Labs (Revelio). Revelio provides workforce data using four primary inputs: employee online professional profiles, company job postings, government data, and firmographic data. We use data from Revelio on workforce demographic composition, salaries, occupational categories, and employee inflows and outflows, as firms do not disclose all the data necessary for our calculations. We use Thomson Reuters WorldScope data for firm financial and performance data. In addition, we use data from the MIT Living Wage Calculator, the Bureau of Labor Statistics, the United States Census Bureau, and other official government sources for information such as State-level minimum wages. These sources and associated methodologies are detailed further in the remainder of the paper.

Our results show a mean employment impact intensity of $56,299 and a median of $57,181. The primary sources of variation are year fixed effects (27% of employment impact is explained by the year in which it is measured), and GICS classification, which when included with year fixed effects, explains 44% of a firm's employment impact. We find a smaller increase in the effect of sub-industry classification, which brings the combined explanatory power to 48%. Notably, we find significant variation in firm employment impact intensity within industries, meaning that managers can drive changes in employment impact through corporate strategy and resource allocation. Adding observable firm-level accounting variables in a model with year and industry fixed effects increases the explanatory power of the model from 44 to 55%. Among those, firm size and a firm's research and development investment intensity are the most significant variables, suggesting that larger firms and firms that invest more in innovation have more positive employment impact. The latter suggests that firms that invest more in building intellectual capital may also invest more in human capital, as a broader strategy to build intangible assets.

Our analysis further decomposes impact intensity by dimension, finding the strongest contribution from wage quality and the smallest driver arising from opportunity impact. We note that this does not mean that the opportunity dimension is less important inside organizations. It only signals that the measurement of employment impact is driven less by the opportunity dimension given the workforce composition in the sample companies.

Exploring the characteristics of employment impact intensity and its relation to the firm, we find that, over a 10-year period, firms with lower initial impact intensity increase this measure at a greater rate than do firms with higher initial intensity, suggesting a narrowing gap between leaders and laggards. Importantly, when graphing the relation between impact intensity and firm size, as measured by total employees, we find a small positive relation between these two measures, suggesting that firm size is not a primary driver of employment impact. Next, we examine the relation between employment impact intensity and commercially available ESG ratings from Refinitiv, Sustainalytics, and MSCI, looking specifically at data provided for the "S" from each of these providers. Correlations between employment impact intensity and ratings from Refinitiv and Sustainalytics are positive and highly significant, while the correlation with MSCI is positive but insignificant. This suggests that ratings, at least partly, reflect employment impact. Still, there are at least two reasons why the employment impact measure provides decision-useful information over and above that contained in commercially available ratings. First, employment impact is measured with transparency and focuses solely on employees, as opposed to other issues that sometimes fall into the "S" of ESG ratings, avoiding concerns about the black box of ESG measurement. Second, employment impact is measured in dollar terms, making it immediately comparable and understandable across firms and time, and an input into financial modeling for investors and companies that seek to optimize not only risk and return but also impact.

Finally, we turn to the question of whether employment impact intensity is associated with employee behavior and firm value. We find a negative and significant relation between employment impact intensity and net employee turnover, suggesting that firms with greater employment impact intensity have greater workforce growth. When decomposing net turnover into inflows and outflows, both measures are positively associated with impact intensity, which could be evidence that firms with higher impact are better at replacing workers who leave. Further exploring these relations by decomposing impact intensity into its components, we find that wage quality is positively (negatively) associated with inflows and outflows (net turnover). Diversity impact is negatively associated with outflows and net turnover, meaning that firms with better demographic representation face greater retention challenges. Location impact is positively (negatively) associated with inflows (net turnover), evidence that firms that have a greater impact on their local labor market also are better at recruiting and retaining workers.

We also find a positive and significant relation between impact intensity and firm valuation as measured by Tobin's Q. These results collectively provide support to management theories that view employee well-being as important for firm competitiveness and performance (Edmans 2011; Gartenberg et al. 2019; Rouen 2020; Lester et al. 2021; Regier and Rouen 2021).

The remainder of the paper is as follows. Section 2 describes our data sources. Section 3 describes our methodology for calculating employment impact. Section 4 presents the results of our analyses. Section 5 reports additional analyses and section 6 discusses caveats to our analysis. Section 7 concludes the paper.

2. Data Sources

Our primary data on workforce composition, location, and wages are from Revelio Labs. Revelio provides approximately 1.5 terabytes of data, measuring estimates of employee inflows and outflows, total number of employees, and salary at granular levels. We rely on these data at the company-location-job category-seniority-gender-race or ethnicity-year level from 2008-2020. A dictionary for Revelio-sourced data is included in Appendix 2.

We augment these data with demographics data from the U.S. Census Bureau and labor force data from the Bureau of Labor Statistics. Living wage data were collected from the MIT Living Wage Calculator.[3] These government data are mapped to the Revelio data by geography, where we rely on Revelio location data for firm establishments. However, Revelio data are sometimes missing state and/or MSA data. When MSA data are missing but state data are not, state-level values of government data are mapped to the Revelio observations. When MSA and state data are missing, country-level data are mapped to the Revelio observations. In addition, Revelio gender-ethnicity pairs are unique in that they do not conform to the standard U.S. Census format. Revelio ethnicity categories are Asian, Hispanic, Non-Hispanic Black, and Non-Hispanic White. The U.S. Census collects three additional categories: Pacific Islander and Native Hawaiian, Native American and Alaskan, and two or more races. To keep the processing of the data tractable and computationally feasible and given the low frequency of certain employee groups, Pacific Islander was included in Asian; Native American and Alaskan was included in white; and two or more were proportionally distributed across all four categories.

[3] MIT living wage data were collected for 2020 and were not available for previous years. To construct a living wage time series, we depreciated the 2020 living wage values by the US Social Security Administration's Cost of Living Adjustments. These adjustments are done on the state-level.

We download accounting data from WorldScope and market data from CRSP. Our data on ESG ratings come directly from MSCI, Sustainalytics, and Refinitiv, and we rely on social scores from each of these datasets.

3. Methodology for calculating *Employment Impact*

We use a combination of data from Revelio, WorldScope, MIT, and U.S. government sources to calculate the five variables of impact that get summed into *Employment impact*. This analysis is an application of the methodological framework previously presented in Freiberg et al. (2020). Adjustments to the methodology were made to accommodate data access limitations, however we have remained as closely aligned with the prior methodology as possible.[4] Here, we describe the calculation of each variable.

1) Wage quality impact

a. Determine the total unadjusted wages paid by the firm in each firm-year observation:

- Total unadjusted wages paid = Sum of (total wages paid in Location_1)[5]

b. Determine the living wage adjustment at Location_1:

- Determine the living wage benchmark for Location_1[6]
- Determine the number of employees earning below the living wage level. If actual wage < living wage benchmark, then this employee is added to the total number of employees earning below the living wage level

[4] For example, this application does not include wage equity, career advancement, or health and wellbeing impact due to data limitations. In addition, rather than using the Equal Employment Opportunity Commission (EEOC) categories of gender, race, and ethnicity to calculate diversity and opportunity impact, we use the categories provided by Revelio. Similarly, the job categories used in Freiberg et al. (2020) were also based on EEOC definitions, while this application uses categorization provided by Revelio (see Appendix 2 for additional information).
[5] Salary data from Revelio Labs is disaggregated by Month, Job Category (e.g., Sales), Demographic group (e.g., Asian Male), and Location (e.g., Boston MSA). Total unadjusted wages are calculated for each group. We then sum the salary data in each observation to determine the total salaries paid across the firm in each year at each firm location. See Appendix 2, Data Dictionary, for additional information.
[6] We rely on data from the MIT Living Wage Calculator (Glasmeier, 2020) for local living wage benchmarks and official government data for local minimum wage levels.

- Calculate the *living wage gap*:
    - Number of employees earning below living wage level * Actual wages paid * -1 = living wage gap
- Calculate *minimum wage credit*:
    - Number of employees earning below living wage level * (Actual wages paid – minimum wage) = minimum wage credit
- Calculate living wage adjustment:
    - Living wage gap + minimum wage credit

c. Determine the marginal utility adjustment at $Location_1$:

- Determine local income satiation level for $Location_1$[7]
- Determine the number of employees earning above the income satiation level
    - If actual wage > income satiation level, then the employee is earning above income satiation level
- Determine the marginal utility adjusted salary paid
    - (Actual salary * marginal utility rate) = marginal utility adjusted salaries paid
- Determine the total marginal utility adjustment:
    - Employees earning above income satiation level * (Actual salary – marginal utility adjusted salary * -1) = total marginal utility adjustment

d. Determine the wage quality impact at $Location_1$:

- Total unadjusted wages paid (a) + living wage adjustment (b) + marginal utility adjustment (c)

e. Repeat steps a – d for each firm location.

f. Total Wage Quality Impact = Sum of wage quality impact (e) at all firm locations

[7] The local income satiation level and marginal utility adjustment is determined using the methodology described in Appendix 3.

2) Diversity impact

a. Determine the total number of employees at the firm

b. Determine the actual number of employees in each gender and race/ethnic group ($group_1$) at the firm[8]

c. Determine the "expected" number of employees in each gender and race/ethnic group by examining local population demographics[9]

- Local demographic representation in $group_1$ * Total number of employees at the firm (a) = Expected number of employees in $group_1$ at the firm

d. Determine the number of "missing" employees in $group_1$[10]

- Expected number of employees in $group_1$ (c) – actual number of employees in $group_1$ (b) = Missing employees in $group_1$

e. Determine the monetized diversity impact for $group_1$

- Missing employees in $group_1$ (d) * Average firm salary = Diversity impact for $group_1$

f. Repeat steps b through e for each demographic group.

g. Repeat steps a through f for each firm location and sum the resulting values to determine the total firm diversity impact.

[8] Demographic groups should be determined based on local regulatory context. For information regarding the groups used in this analysis see Appendix 1 Data Dictionary. For purposes of illustration, we use "$group_1$" to represent an individual demographic group, such as Asian Female. The group Asian Male, similarly, could be described as $group_2$. As evident in the methodology steps, calculations should be repeated for each demographic group and summed for the total firm impact figure.
[9] We use data from the U.S. Census to determine local population benchmarks. For example, if 10% of the local population is Asian female according to the Census, the firm benchmark is 10% for this group.
[10] If this number is positive, there is no under-representation of this group, and the impact is zero (0).

3) Opportunity across job category impact

a. Determine the average annual salary paid at the firm for each Job Category

- Total unadjusted salaries paid in Job Category$_1$ / Total employees in Job Category$_1$ = Average annual salary in Job Category$_1$

b. Rank each Job Category by average salary and determine the median category

c. Establish a “high salary group” and “low salary group”

- Employees in Job Categories earning above the median are in the “high salary group” and those earning below are in the “low salary group”

d. Determine the percentage of employees in demographic group$_1$ at the firm

e. Determine the expected number of employees in group$_1$ in the “high salary group”

- Percentage of employees in group$_1$ at the firm * Total employees in “high salary group” = Expected number of employees in group$_1$ in “high salary group”

f. Determine the actual number of employees in group$_1$ in the “high salary group”

g. Determine the “missing” employees in group$_1$ in the “high salary group”

- Expected number of employees in group$_1$ in “high salary group” (d) - actual number of employees in group$_1$ in the “high salary group” (e) = “missing” employees in group$_1$ in the “high salary group”[11]

h. Determine the monetized opportunity across job category impact for group$_1$

- “Missing” employees in group$_1$ in the “high salary group” (f) * (Average salary in “high salary group” – Average salary in “low salary group) * -1

i. Repeat steps c through g for each demographic group.

[11] If this number is positive the impact is zero. There is no additional “credit” or positive value given.

j. Repeat steps a through h for each firm location and sum the resulting values to determine the total firm opportunity across job category impact.

4) Opportunity across seniorities impact

a. Determine the total number of employees in Seniority Level 2[12]

b. Determine the number of employees in $group_1$ at Seniority Level 2

c. Determine the percentage of employees in $group_1$ at the firm

d. Determine the expected number of employees in $group_1$ at Seniority Level 2

- Total employees at Seniority Level 2 (b) * Percentage of employees at $group_1$ at the firm (c)

e. Calculate the number of "missing" employees from $group_1$ at Seniority Level 2

- Expected number of employees in $group_1$ at Seniority Level 2 (d) – Number of employees in $group_1$ at Seniority Level 2 (b) = "missing" employees from $group_1$ at Seniority Level 2

f. Calculate the monetized opportunity penalty for Seniority Level 2

- "Missing" employees from $group_1$ at Seniority Level 2 (e) * (Average salary in Seniority Level 2 – Average Salary in Seniority Level 1) * -1

g. Repeat steps d and e for Seniority Level 3 and Seniority Level 4.

h. Repeat steps a through f for each demographic group.

i. Repeat steps a through h for each firm location and sum the resulting values to determine the total firm opportunity across seniorities impact.

[12] Revelio Labs calculates four seniority levels within each job category. The most junior level is 1 and most senior level is 4.

5) Location impact

a. Determine the number of employees at each firm location

b. Identify total employed individuals from local unemployment statistics for firm location

c. Identify total unemployed individuals from local unemployment statistics for firm location

d. Determine the incremental wages received due to firm employment at firm location $_l$

- Average annual salary for firm employee - Average annual salary at minimum wage[13] = incremental wages received

e. Determine the hypothesized unemployment rate without firm job creation at firm location $_l$.

- (Total unemployed persons (b) + Total employees at firm location (a)) / (Total employed persons (b) + Total unemployed persons (c)) = hypothesized local unemployment rate without firm job creation.

f. Determine the monetized location impact

- Incremental wages received due to firm employment (d) * hypothesized unemployment rate without firm job creation (e) * Number of employees (a)

g. Repeat steps a through f each firm location and sum the resulting values to produce the total location impact value.

6) Employment Impact

[13] This methodology has been adapted from the calculation presented in Freiberg et al (2020). The time series covered in this paper (from 2008 – 2020), made an accurate accounting of Unemployment Insurance across years and MSAs prohibitive. Therefore, in this analysis we use local minimum wage as a proxy for the value of the local social safety net to calculate location impact for each firm-year observation.

a. Sum values in Steps 1 through 5 to produce the total employment impact for the firm.

Table 1 reports descriptive statistics for *Employment impact* and its components for the 22,322 firm-years in our sample. Mean (median) *Employment impact* is \$545 million (\$82 million) and is right-skewed with a maximum impact of \$40.2 billion, hence our use of logged values in our analysis. *Wage quality* provides the largest positive impact, with a mean (median) impact of \$695 million (\$120 million). *Diversity* has the largest negative impact, with a mean (median) impact of -\$173 million (-\$37 million).

4. Analysis and Discussion

4.1 The Measurement and Distribution of Employment impact intensity

We define employment impact intensity as the total employment impact scaled by the total number of employees included in the impact calculation. Total employees is a natural deflator to make impact comparable across firms. When measuring impact, it is important to scale the value of that impact by the unit of activity so that firms can be more directly compared. The unit of activity is difficult to observe when calculating environmental impact as it is often indirect or unobservable, such as kilowatts per hour for energy consumption or miles covered for transportation. Therefore, environmental impact is often scaled by revenue as a proxy for this activity (Frieberg et al. 2021). The impact-weighted accounts Product Impact Framework also proposes scaling by revenue, as this provides a relevant unit of analysis for consumer and societal impact from the associated product or service (Serafeim and Trinh 2021).[14]

[14] The issue with scaling by revenue is that it can punish successful firms or reward unsuccessful firms when the deflator is impacted by performance unrelated to the impact of the firm (e.g., a firm may produce and ship a product that fails to sell, which would reduce revenues while increasing environmental impact at a rate similar to what would be expected of a successful product).

Employment impact, on the other hand, has the intuitive and observable unit of activity of the number of employees. Figure 1a shows the distribution of the sample's employment impact intensity. The data are normally distributed with a mean of $56,299 and a median of $57,181. The standard deviation is $15,009. To make the analysis more comparable and easier to interpret, we use the natural log of employment impact intensity going forward.[15] Figure 1b reports the distribution of logged employment impact intensity. Here, the mean is 10.89, and the median is 10.95. Logged employment impact intensity has a standard deviation of 0.32.

4.2 Drivers of employment impact intensity

We next examine macroeconomic characteristics that are likely to drive employment impact and intensity. Firms are likely to make investments in human resources based, in part, on what will maximize profits and provide competitive advantages, but they are also bounded by macroeconomic trends and the nature of the labor market within the industry in which they operate. To examine the relation between employment impact intensity and these variables, we regress logged employment impact intensity on indicators for each of the years in our sample and indicators for the industry and sub-industry in which the firm operates. Table 2 reports the adjusted R-squared, a measure of how powerful the independent variables are at explaining logged employment impact intensity. The first model includes only year fixed effects. The explanatory power in this model is 27%. The high explanatory power of this model is due, in part, to a monotonic increase in employment impact over time in our data. In untabulated analysis, we find that when decomposing the total employment impact intensity to each element, it is the steady

[15] Results remain unchanged when using raw employment impact intensity.

increase in total wages (a component of wage quality) during our sample period that is driving the high explanatory power of the year fixed effects.[16]

The second model adds industry effects using the GICS classification. Adding these effects to the year effects increases the explanatory power of the model to 44%, suggesting that industry membership is an important driver of a firm's employment impact intensity. Given the importance of industry in determining employment impact intensity, we drill down further in the third model and replace the 69 GICS industry classifications with the 158 GICS sub-industry classifications. Surprisingly, the increase in explanatory power is rather small, increasing from 44% to 48%. Given the granularity of the sub-industry classification, this small increase means that, while industry plays an important role in determining employment impact intensity, much of the variation in intensity is driven by firm characteristics. This suggests that firms have significant idiosyncratic influence over their total intensity that is not driven by macroeconomic factors.

Because of the importance of industry in driving employment impact, we describe the distribution of employment impact across industries in Figure 2. Figure 2, Panel A visualizes average employment impact across industries, as well as the ratio between the first and third quartiles of employment impact intensity within the industry (the interquartile range). For interpretability, we report raw employment impact in dollars. IT Services has the highest average impact of almost $70,000 per employee (Figure 2, Panel A), followed closely by Software, Pharmaceuticals, and Healthcare Technology.

There exists large variation across companies within these industries, though, as shown by the interquartile range (the orange line) representing the difference in employment impact intensity

[16] This increase in wages is due, in part, to historically low interest rates during our sample period, which resulted in business expansion and hiring. In addition, according to the Bureau of Labor Statistics, the unemployment rate steadily declined during our sample period, resulting in higher demand for workers and higher wages.

by the firm in the third quartile and that in the first quartile for firms in the same industry. For example, within pharmaceuticals, the firm in the third quartile has an employment impact intensity that is 45% higher than the firm in the first quartile. Industries that employ significant numbers of low-wage workers have the lowest employment impact intensity. Airlines and Food and Staples Retailing are within the 5 lowest performing industries, with employment impact intensity of $39,356 and $46,512 respectively. These industries also have significant variation across firms, as shown by the interquartile range in Figure 2 Panel A.

To further understand what is driving intensity at the industry level, in Figure 2, Panel B, we visualize the average components of employment impact at the industry level. Across industries, wage quality is the primary driver of employment impact intensity. On the other hand, all industries, on average, are penalized for their lack of diversity, and most industries incur a penalty of between $10,000 and $27,000 per employee. Opportunity across seniorities also results in penalties across industries, although it is a much smaller penalty. Location creates a small, but noticeable positive impact on intensity. To gain insight into the relation among employment impact dimensions, we examine diversity and opportunity impacts per employee in Figure 2, Panel C. We are especially interested in understanding this relation due to the large negative contribution of diversity impact to total employment impact intensity, and the interrelated nature of diversity and opportunity performance within firms. We use data from 2019 and find that diversity and opportunity impacts are positively related.[17] Firms that underperform in diversity impact (by employing a workforce that does not represent local demographics) also have poor opportunity performance, as measured by comparing overall workforce demographics with representation in

[17] We combine opportunity impact across seniorities and opportunity impact across job categories for this analysis.

different job categories and seniorities. This relation indicates the importance of a comprehensive approach to diversity and inclusion within firms.

Figure 2, Panel D shows employment impact intensity in the Hotels, Restaurants, and Leisure industry in 2019 for 32 US-based firms to demonstrate the variation within industries. In this sample, the leading company (Extended Stay America, Inc) has an employment impact intensity of $97,747 per employee, which is more than 10 times that of the lowest-performing company. The mean employment intensity is $76,336 among companies in the first quartile, compared to $52,881 among those in the third quartile. This suggests significant opportunity for firms to distinguish their employment impact performance based on human capital decisions and warrants further research to study firm characteristics and other factors that may be related to over- and under-performance.

In Figure 3 we compare employment impact intensity in 2009 and 2019 to examine how employment impact varies over time. Our sample includes 1,301 firms with available data in 2009 and 2019. Given the average employment impact intensity of $39,884 and $62,902 in 2009 and 2019, respectively, the upward trend shows that firms with above-median employment impact intensity in 2009 improve at a slightly lower rate than do firms with below-median intensity. For example, a firm with impact intensity of $20,000 in 2009 would improve to almost double the impact intensity in 2019. On the other hand, a firm with impact intensity of $60,000 in 2009 would improve by a rate of 1.5 by 2019.

Is higher positive employment impact the consequence of firms having more resources? If that is the case then we expect a strong relationship with firm workforce size and profitability. We first analyze whether firm size, as measured by the number of employees at the firm, is a driver of higher employment impact intensity. Figure 4 reports the relation between employment impact intensity and the natural log of total employees for 573 firms.[18] The slope of the line of fit indicates that firm size is a driver of employment impact intensity with larger firms having moderately more impact, suggesting that firm size plays a role in providing an opportunity to improve employment impact. This relationship is small, however, indicating that there are not substantial economies of scale at play regarding workforce size and employment impact.

Next, we examine the relation between employment impact intensity and operating income per employee. We use operating income per employee as a measure of profitability for ease of comparison with employment impact per employee. Figure 5 graphs employment intensity and operating income for 1,649 firms in 2019 and documents a small positive relation between impact and profit. This relation suggests that profitability plays only a very limited role in describing firms' capacity to create employment impact.

4.3 Determinants of employment impact intensity

Table 3 shows the results of models that use employment impact intensity as the dependent variable. Explanatory variables include year and industry effects and several firm-year level financial characteristics. We include measures of firm profitability, capital structure, investment profile in capital and research and development expenditures, payouts, and size. Model 1 does not include any fixed effects, while model 2 introduces year effects and model 3 adds industry effects. A few results are noteworthy. First, the explanatory power of the model increases from 44 to 55% when the financial variables are added in addition to the industry and year effects. Second, firm size and R&D expenditures over sales are the two variables that are consistently positively correlated with employment impact. The estimated coefficient on the firm size variable suggests a

[18] We excluded firms with fewer than 5,000 and greater than 350,000 total employees to eliminate outliers.

close to 7% increase in employment impact for a doubling of firm sales. The positive association with R&D expenditures suggests that firms that invest in innovation are more likely to have more positive employment impact. While there is a negative association between impact intensity and both capital expenditures and leverage, these results are driven by the absence of industry effects, because industries where companies invest more in capital expenditures and have higher leverage have lower employment impact (as evident in the third model presented in Table 3).

4.4 Employment Impact Intensity and Social Ratings

The measurement of employment impact intensity for a large number of publicly traded companies provides an opportunity to compare the dollar value of employment impact per employee with existing measures of firms' commitments to social issues, as presented by three commercially available ESG ratings providers: Refinitiv, Sustainalytics, and MSCI. Since investors and analysts rely on these ratings to understand firms' social commitments, it is of interest to understand how they relate to employment impact intensity. All three of these databases use various publicly available data points to calculate firm-year-level social ("S") scores. The correlations between the scores are all positive and highly significant. The correlation between the Refinitiv and Sustainalytics scores is 0.49. The correlation between Refinitiv (Sustainalytics) and MSCI is 0.19 (0.20) (see Table 4).

Table 5 examines the relation between employment impact intensity and the three social ratings, reporting the estimated coefficients and t-statistics from regressing employment impact intensity on the individual social ratings. The first row reports estimates from a model based on variation across the whole market, while the second row reports estimates from a model that includes industry fixed effects, thereby estimating the coefficient within industry. Given the important time trend documented in Table 2, in both specifications, we include year fixed effects. When examining the relation between employment impact intensity and social scores across the market, we find that these social scores do, in part, capture employment impact intensity. All are positively related to employment impact intensity with the Refinitiv (Sustainalytics) score statistically significant at 1% (5%). When including industry fixed effects, and thereby examining average effects within industries, the relation between employment impact intensity and social score increases for all three measures. While the coefficient on the Refinitiv score remains largely unchanged, the statistical significance increases sharply. The coefficient for the Sustainalytics score increases from 0.0027 to 0.0033, while the t statistic increases from 2.08 to 4.20, meaning that the relation between employment impact intensity and this social score is statistically significant at 1% when examining the average within-industry relation. Both the coefficient and the t-statistics on the MSCI score more than double when examining the within-industry average effect, although the coefficient remains statistically insignificant at conventional levels. Taken together, these results suggest that commercially available social scores partly account for employment impact intensity, and these relations become stronger when examining the within-industry relations. This result stands in contrast to the relation observed between environmental impact and environmental commercial ratings (Freiberg et al. 2020) suggesting a closer alignment between commercial ratings and impacts when it comes to S rather than to the E part of ESG. These results may be surprising to some who consider environmental impact measurement more advanced than social impact measurement. Further research is needed to determine the relation between specific components of commercially available S scores and employment impact intensity.

4.5 Employment impact intensity and employee turnover

How does employment impact intensity relate to employee decision-making? We examine this question by documenting the relation between net turnover and employment impact intensity, with the expectation that, if employment impact captures the opportunities and benefits a firm creates for its employees, higher impact intensity will be associated with lower turnover.

Table 6 documents the relation between employment impact intensity, employee inflows and outflows scaled by total employees at the firm, and net employee turnover, measured as the number of employees who have left their jobs minus the number who were hired, scaled by total employees at the firm. We find that the relation between employment impact intensity and net turnover is negative and significant. When decomposing net turnover, we find that both employee inflows and outflows scaled by total employees are positively associated with impact intensity, although the magnitude of the association with inflows is greater. With the limitations of our current data, it is impossible to provide causal evidence to explain these relations, but one potential explanation is that firms with greater impact are able to recruit and replace higher-quality employees, who are more desirable in the labor market, and therefore more likely to leave the firm.

To further understand the relation between employee turnover and impact intensity, Table 7 examines how turnover relates to the components of impact intensity.[19] Consistent with the above findings, wage quality is positively (negatively) associated with inflows and outflows (net turnover). The diversity impact penalty is negatively associated with outflows and net turnover. Further research is needed to determine if there are demographic trends related to this finding, as our current analysis does not identify whether outflows are evenly distributed across the firm's workforce, or whether there are certain groups that are more or less impacted. There are many

[19] In this analysis, we include the same controls as in Tables 5 and 6 but do not report them for the purpose of brevity.

hypotheses that should be explored regarding diversity and turnover, including the role of family-friendly workplace policies in retaining female workers and caregivers, varying attrition rates across employees of different racial and ethnic backgrounds, and the interplay between diversity, organizational culture, and turnover (Leonard, 2006; Doede, 2017; McKay, 2007; Jones, 2005). Location impact is positively (negatively) associated with inflows (net turnover), suggesting that firms with greater positive job creation impact on their communities are better at recruiting and retaining talent.

We also examine the relation between impact intensity and net turnover in greater detail in Figure 6 by running the analysis at the industry level. We find that the negative relation between impact intensity and net turnover is highest for the Software industry, but that the relation is not negative for all industries. Among all industries, Health Care Providers and Services has the strongest positive association between impact intensity and net turnover. One potential explanation for these relations is that human capital, as an asset, is valued more highly in knowledge-based industries like Software. In these industries, managers may make decisions that improve employment impact and mitigate turnover. On the other hand, many of the industries in which the relation between turnover and impact is positive, such as Health Care Providers and Services and Retail, traditionally experience annual turnover rates greater than 60 percent, suggesting that employment impact fails to mitigate these already challenging trends (BLS 2021). In future analyses, we will examine these relations in more detail, as well as explorehow employment impact intensity relates to other employee-related measures such as net promoter score or employee satisfaction level.

4.6 Employment impact intensity and corporate value

Employment expenses as a share of revenue are among the largest expenses for most firms (Regier and Rouen 2021). As a result, lowering those expenses mechanically increases the current profit of a firm. At the same time, spending more money on employees can reduce costly turnover and can represent an investment for the firm that could raise productivity and innovation, and drive new business opportunities. That investment can come in many forms, including impact that improves working conditions and provides opportunities for employees.

Table 8 examines the relation between employment impact intensity and Tobin's Q, which represents a measure of the market value of assets over the book value of assets (Tobin's Q increases as expected growth increases and perceived firm risk decreases). We find that the relation between employment impact intensity and Tobin's Q is positive and significant, suggesting that firms with greater employment impact intensity have higher valuations.

Examining the relation between employment impact intensity and the value of the firm (i.e., Tobin's Q) provides a useful lens to understand the circumstances under which impact intensity might be of most use to investors and managers. To that end, in Figure 7 we report the results of re-running the above analysis by industry. We find that firms in the Air Freight & Logistics industry have the strongest positive relation between impact intensity and Tobin's Q, while those in the Health Care industry have the lowest. We find this industry analysis to be somewhat surprising in relation to the findings in Figure 6. For example, while Air Freight & Logistics has the strongest statistically positive relation between impact intensity and Tobin's Q, it also has a significantly positive relation between impact intensity and net turnover. On the other hand, the Building Products industry has a significantly positive relation between impact intensity and Tobin's Q, and a significantly negative relation between impact intensity and net turnover. While a higher Tobin's Q is objectively positive for firm management, these results suggest that managers' objective with net turnover may not be linear and may be industry-, or even firm-specific. In other words, there may be an optimal level of net turnover that maximizes firm value. We plan to explore this possibility in future research.

As with the turnover analysis, to better understand the drivers of the relations documented above, we conclude our empirical analysis by examining how Tobin's Q relates to the unique dimensions of employment impact intensity. Table 9 documents the results of regressing Tobin's Q on each impact component separately. We find that the relation in Table 8 is, in large part, driven by wage quality. Wage quality is statistically positively related to Tobin's Q. Similar to the findings reported in Table 7, firms with greater location impact also have higher valuations, possibly because these firms are greater at recruiting and retaining high-quality local workers (as reported in Table 7), leading to increased productivity.

5. Additional Analyses

Throughout this paper, employment impact is scaled by the total number of employees to enable comparison across firms along the most direct dimension. In untabulated analysis, we explore scaling employment impact by total unadjusted wages paid by the firm. This approach has several benefits and limitations. Human capital is most frequently viewed as an expense, which makes total wages paid an intuitive scaling mechanism. This analysis allows managers to determine how much positive impact is created for every dollar spent via wages. While this may be a valuable metric for managers, there are drawbacks to the approach for the purposes of impact-weighted accounting. For example, total unadjusted wages paid is not a comprehensive account of human capital investment, as it does not include other forms of compensation, training and development costs, or recruitment and retention expenses. Also, scaling total employment impact by total unadjusted wages paid presents a potential perverse incentive to firms to decrease their total wage bill (thereby reducing the scaling denominator and increasing their relative employment impact intensity).

Our analysis of employment impact scaled by total wages shows significant differences from employment impact scaled by total employees. We find mixed associations with social scores from Refinitiv, MSCI, and Sustainalytics. We find negative associations with Tobin's Q. Relations between employment impact scaled by total wages and turnover are largely insignificant. These results are not surprising, as they reiterate many of the aforementioned limitations, as well as previous research that demonstrates the positive relation between spending towards human capital management (measured by personnel expenses) and firm performance (Regier and Rouen, 2021).

6. Caveats

Several caveats apply to the methodology and analysis in this paper. We outline several here and expect that this work will spark additional dialogue regarding corporate employment impact which will lead to strengthened analytical efforts in the future. A first objection may be related to reporting and selection bias, as we removed firm-year observations that did not include employee count, industry, or sales data in WorldScope. Additionally, we omitted firms with an employee ratio (*er*) less than 0.1 or greater than 1.2, with *er* calculated as the total employees calculated by Revelio Labs divided by the total employees reported to WorldScope. This step is done to remove observations with insufficient or inaccurate measures of employment. An important feature of Revelio's data is that workforce figures include contingent (or contract) workers, while this is not a requirement of WorldScope data. Therefore, eliminating companies with a high *er* (1.2 or above) may have resulted in under-sampling companies with a large contingent workforce, which has a relationship with employment quality that is currently under significant debate and study. Despite this potential sampling bias, the inability to distinguish between contingent and direct employees within the data could have led to misleading results in our analysis, and we therefore maintain that this approach was the most rigorous available to us within the constraints of reporting and data availability.

Similarly, an objection related to selection bias may arise from the choice to omit observations with low *er* values (0.1 or below). WorldScope data includes all firm employees regardless of their location, while Revelio data used in our analysis includes only US-based employees. Therefore, we may have under-sampled firms with a large number of employees based outside of the US by excluding low *er* values. The potential risk of miscalculating the core dimensions of employment impact (e.g., diversity impact) by analyzing employees across unknown locations outweighed the risk of this potential sampling bias.

An additional objection to the results of this paper is that we analyze only the employment impact intensity from a firm's direct operations. We do not attempt to measure any upstream employment impact that occurs within a company's supply chain due to extremely limited data and lack of consensus regarding attribution.

Readers may also note the potential "threshold effect" that arises from the living wage adjustment methodology used in this analysis. Wages paid at or above the living wage benchmark are counted at a one-to-one value, up to the point of local income satiation. This means that there is no *additional* benefit incorporated into the methodology for a wage paid at the living wage benchmark compared to a wage paid at a significantly higher value. One could argue that the wellbeing impact of wages is not static between living wage and income satiation. Additionally, the adjustment to wages paid below living wage is applied linearly, such that there is no *additional* negative penalty to paying a wage that is $1 below the living wage versus $2 below. This problem is partially mitigated by the use of the minimum wage credit described in the methodology section above. However, the limitations of our approach are well-noted and are being explored for potential application in future analyses.[20]

Finally, it should be noted that the use of the minimum wage within the monetization methodologies of the wage quality impact dimension and the location dimension is heavily influenced by local public policy and should thus be interpreted with care. The use of minimum wage in these calculations also introduces a potential perverse incentive for firms to advocate for lower (or stagnant) minimum wage levels in their areas of operations (which in turn increases their respective minimum wage credits in the wage quality dimension and incremental wages earned in the location impact dimension).

7. Conclusion

This paper demonstrates that large scale monetized impact analysis is feasible, and that results can provide meaningful insights for investors, managers, and the broader stakeholder economy. Employment impact intensity is calculated for 22,322 firm-year years, providing a robust sample for industry-level benchmark analyses. We find significant heterogeneity within industries, proving that firms can make strategic changes to increase the positive value created through their employment practices. We also analyze the relationship between employment impact intensity and key firm characteristics such as employee headcount, sales, research and development spending, operating income, net turnover, and Tobin's Q, as well as commercially available Social scores from ESG raters. Presenting employment impact intensity in dollar terms

[20] We are partnering with Shift and the Capitals Coalition, organizations that are leading the Accounting for Living Wage project to better reflect living wage impact within accounting systems.

allows firms, investors, and policy-makers to effectively calculate future risks and opportunities associated with human capital practices.

As employment data become more widely available, future analysis that includes wage equity, workforce health and wellbeing, and career advancement should be prioritized to provide deeper understanding of firm performance. These additional impact dimensions, as outlined in Freiberg et al. (2020), are critical to rigorous analysis of employment quality. In addition, insight into employment status (e.g., part-time, contingent, and contract workers), as well as a broader definition of employment impact to include a firm's supply chain workforce, is critical to wholly grasping the extent of positive and negative impacts created by companies in the global economy.

As previously noted, these additional analyses will likely result in significantly different results in firm performance both across and within industries. Workforce demographics are highly varied by industry, with female workers comprising a disproportionate number of the voluntary part-time workforce in the United States (citing childcare and family/personal obligations as a primary reason for part-time status) (BLS 2017; BLS 2019; Penner 2008; Cortes 2018). Additionally, Black and Latino workers are more likely to work part-time schedules, with minority women most likely to be in low-paying service work (Economic Policy Institute 2020; Cajner et al. 2017; Cohen and Casselman 2020). For the purposes of this analysis, we assume that all employees work a full-time (40 hours per week) schedule. However, in 2020 an estimated 36% of workers in the Hotels, Restaurants, and Leisure industry were part-time status, working an average of 26 hours per week (BLS 2020). This distinction has important implications for impact calculations across all dimensions. In addition, worker health and wellbeing impact, once included in future analysis, is strongly influenced by worker status (for example, Pew Research Center reports that only 33% of part-time workers have access to paid sick leave or vacation, compared to 78% of full-time workers). Future analysis that incorporates a broader set of impact dimensions and considers worker status will provide more rigorous results for interpretation and use among decision-makers.

Lastly, in future research, we plan to replicate the analysis by adding non-US geographies, with adjustments made as needed for local contexts. This application will provide further evidence for the feasibility of employment impact-weighted accounting, as well as generate insights regarding the comparative value of workforce externalities among firms working in multiple locations. In the context of a global, interconnected economy, this is critical to a broader understanding of how companies influence employees throughout the world through their human capital strategies.

Figure 1: Distribution of employment impact intensity

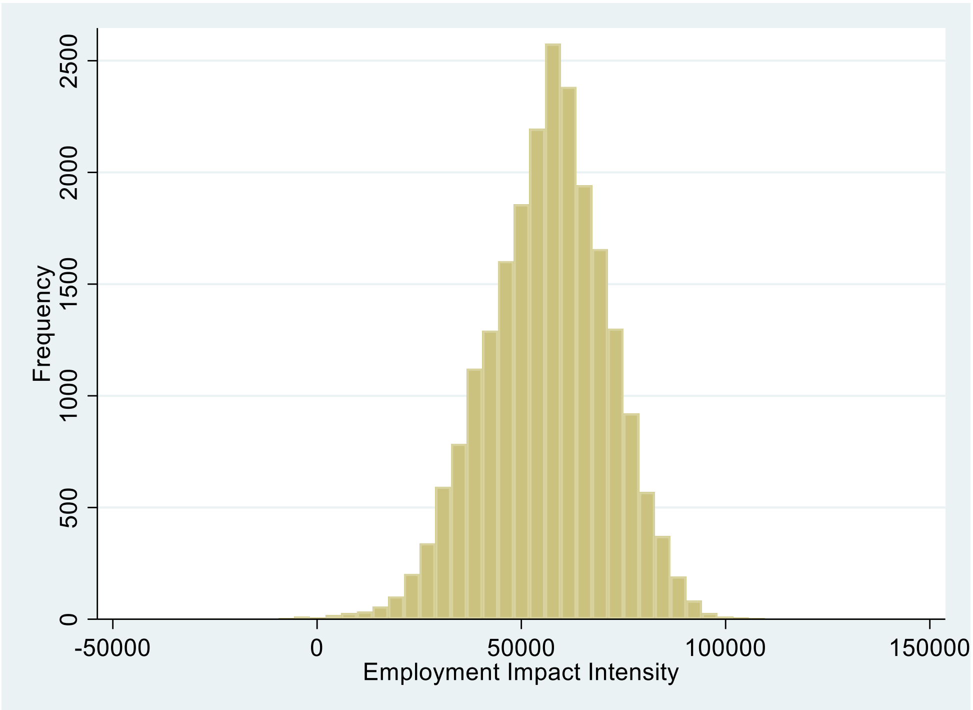
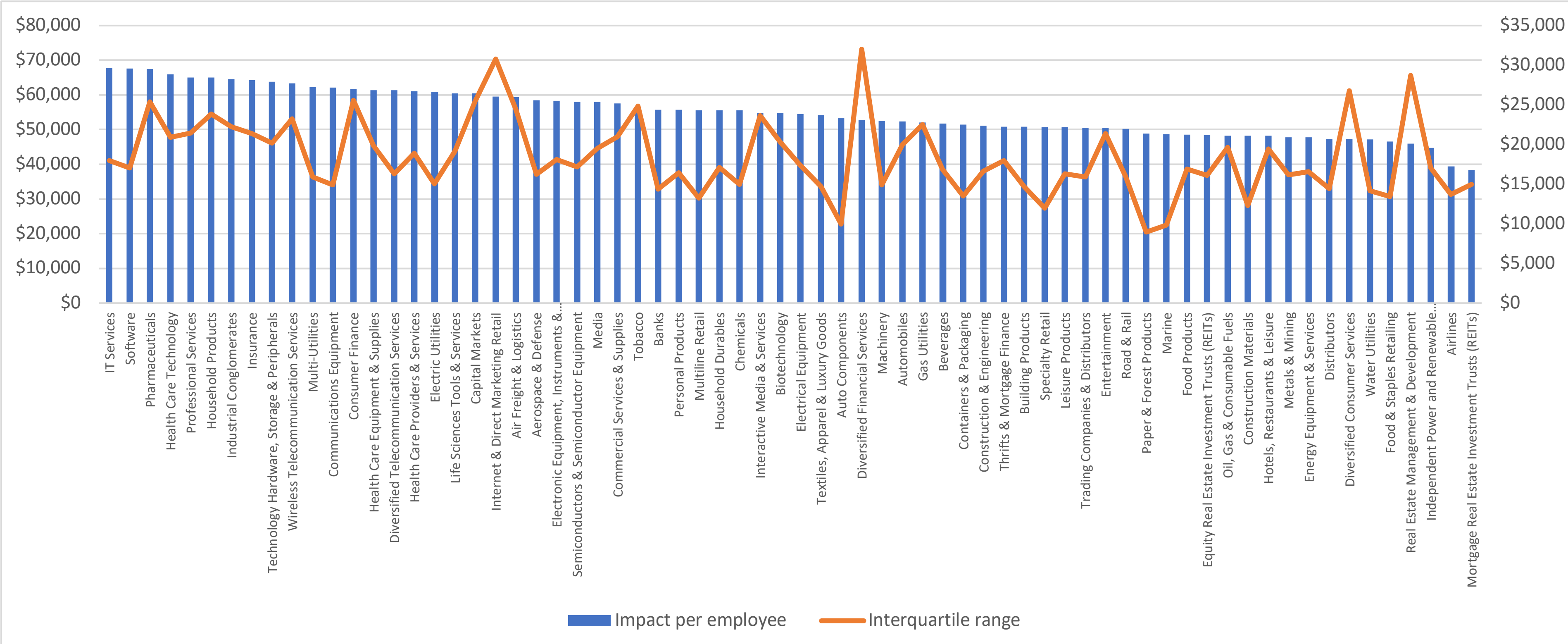
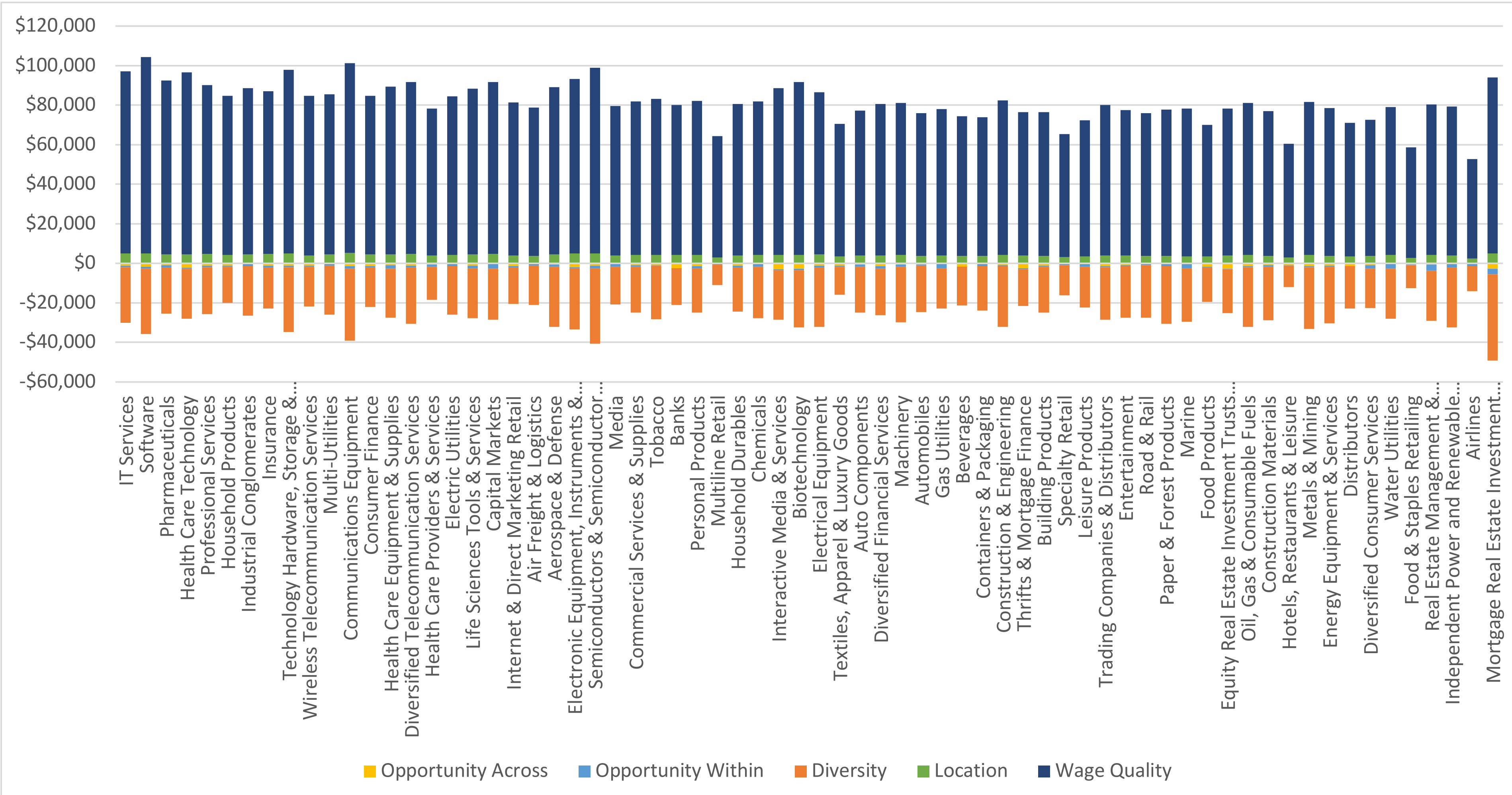


Figure 2: Employment impact intensity by industry

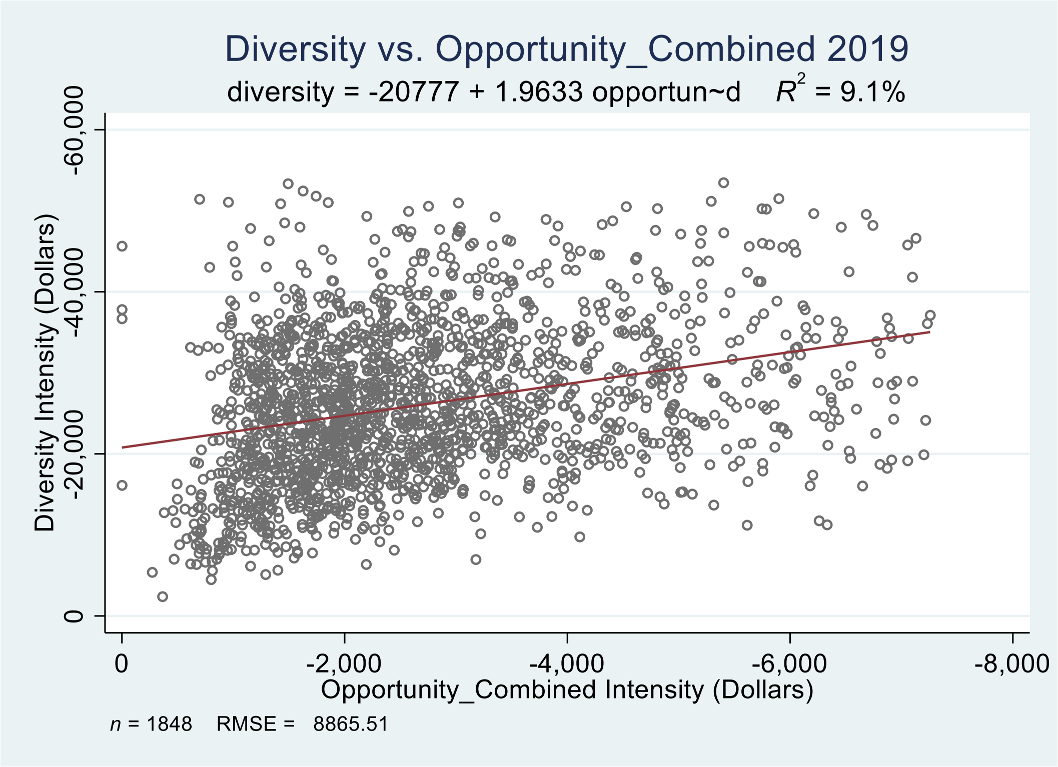
Panel A: Total employment impact intensity



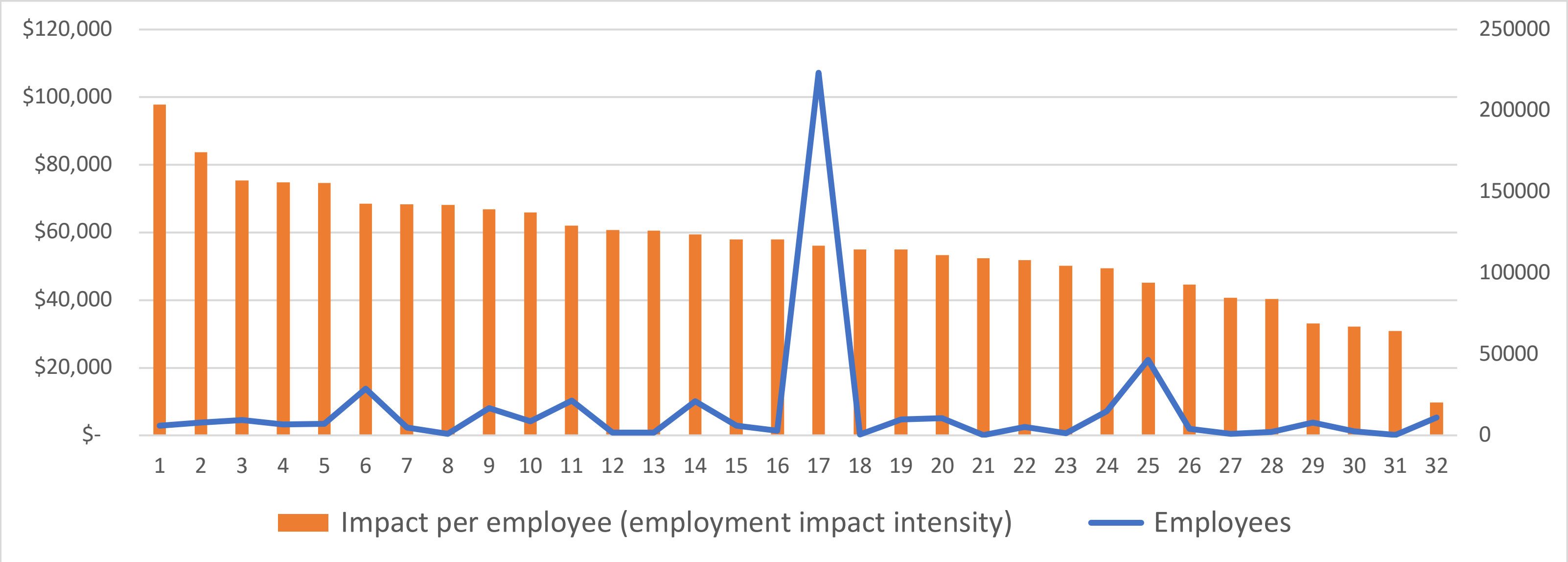
Panel B: Components of employment impact intensity



Panel C: The relation between Diversity and Opportunity impact (2019)



*Panel D: Employment impact intensity in Hotels, Restaurants, and Leisure Industry (2019)**



*Hotels, Restaurants, and Leisure Industry firms in the top quartile of employment impact intensity (2019)**

Company Name	Employees	Impact per employee	
EXTENDED STAY AMERICA INC	5955	$	97,747
SHAKE SHACK INC	7702	$	83,671
BOYD GAMING CORPORATION	9350	$	75,279
INTERNATIONAL GAME TECHNOLOGY PLC	6902	$	74,725
LAS VEGAS SANDS CORP.	7120	$	74,639
CAESARS ENTERTAINMENT CORP	28762	$	68,424
SCIENTIFIC GAMES CORP	4857	$	68,251
RESTAURANT BRANDS INTERNATIONAL INC	774	$	68,193

*Firms domiciled in US only

Figure 3: The change in employment impact intensity from 2009 to 2019

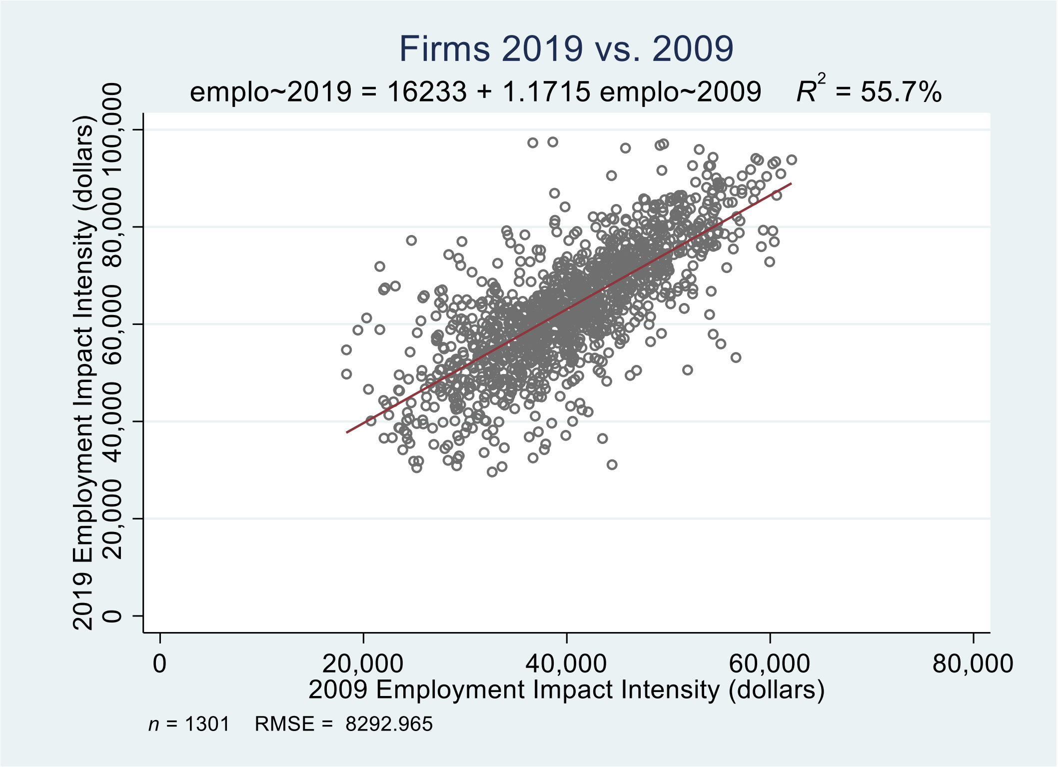


Figure 4: The relation between employment impact intensity and firm size as measured by headcount (2008-2020)

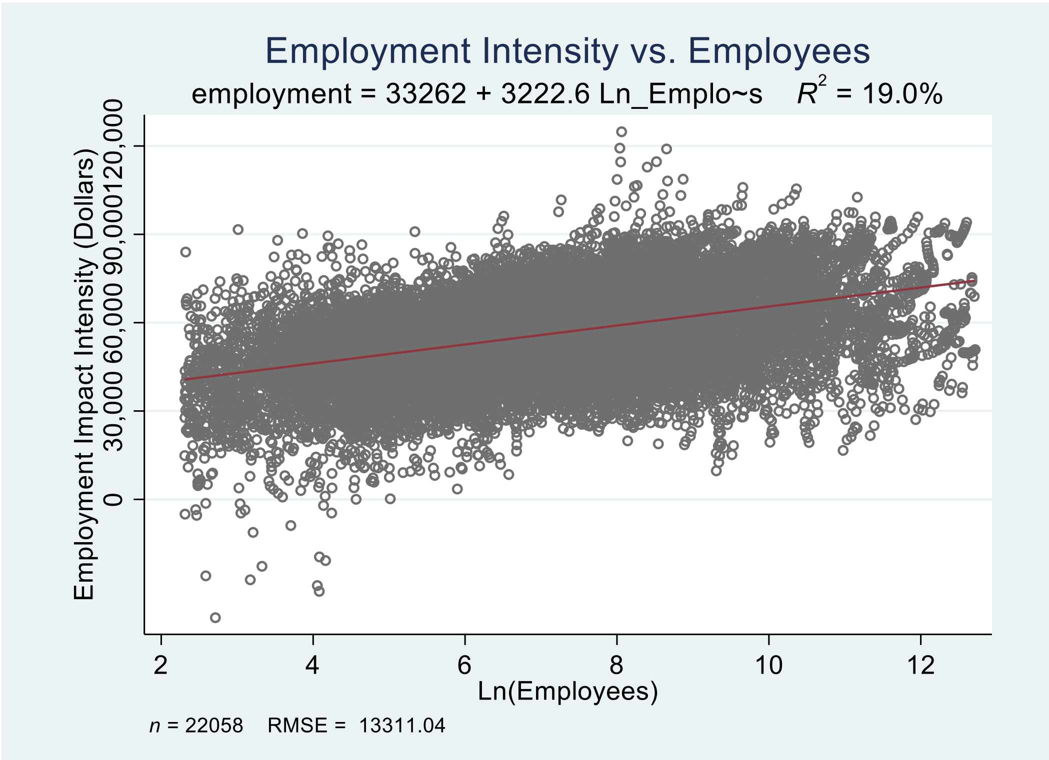


Figure 5: The relation between employment impact intensity and income per employee (2019)

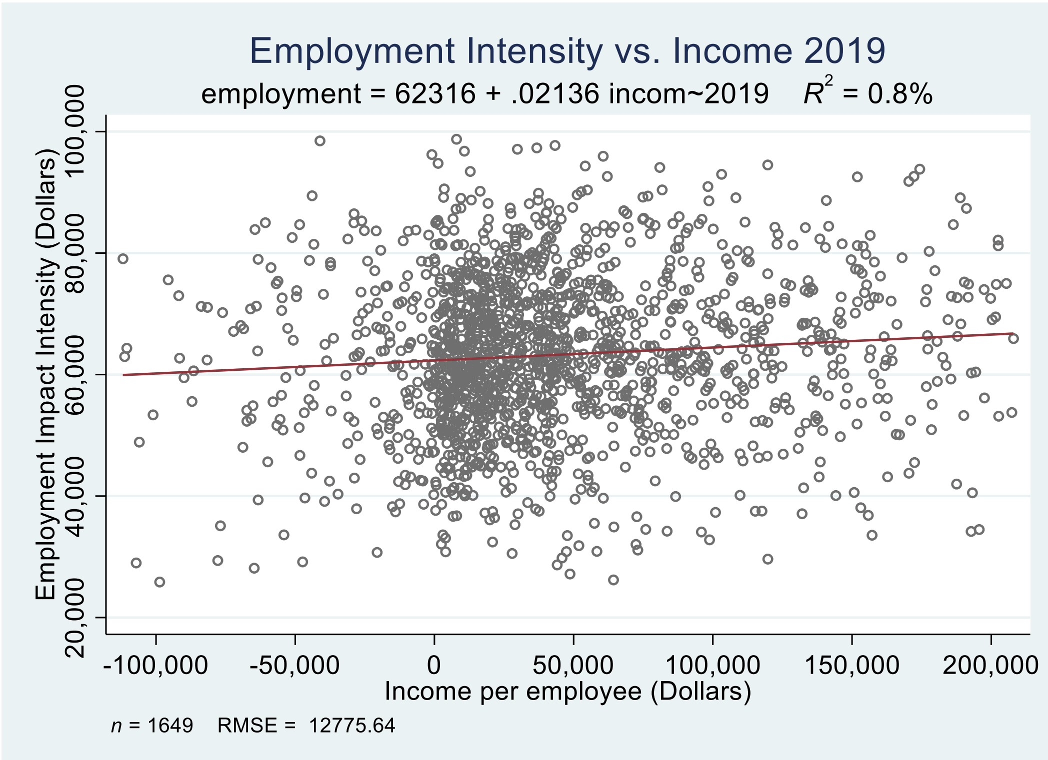


Figure 6: The relation between employment impact intensity and net turnover by selected industry

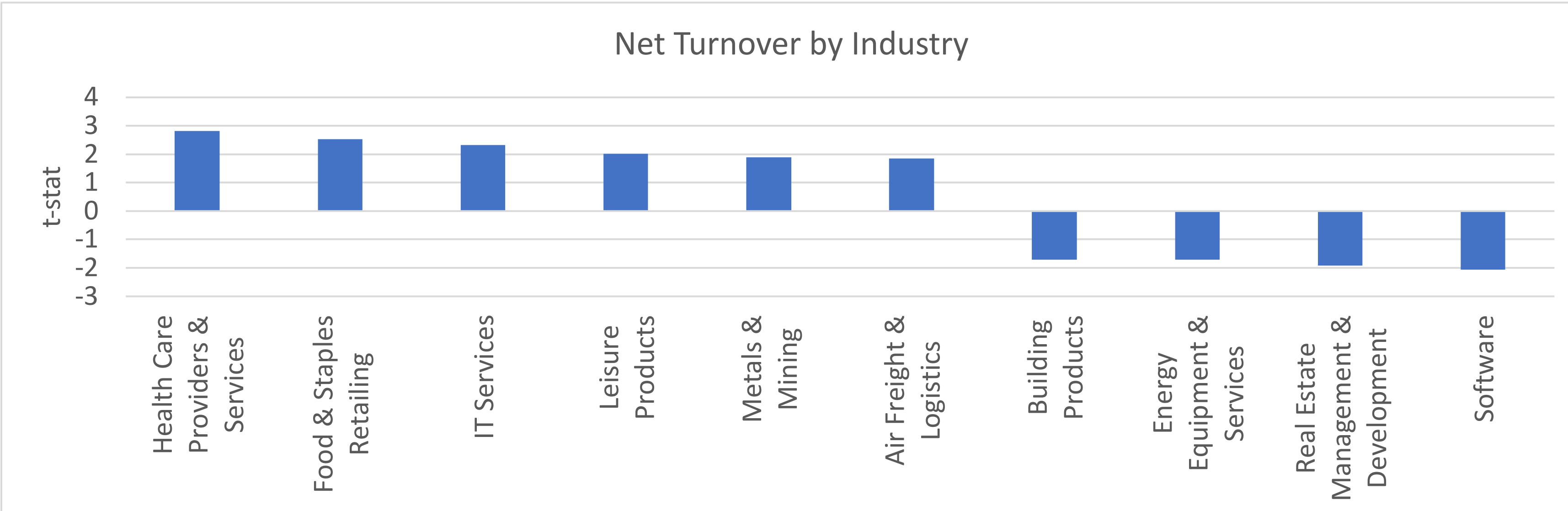


Figure 7: The relation between employment impact intensity and Tobin's Q by selected industry

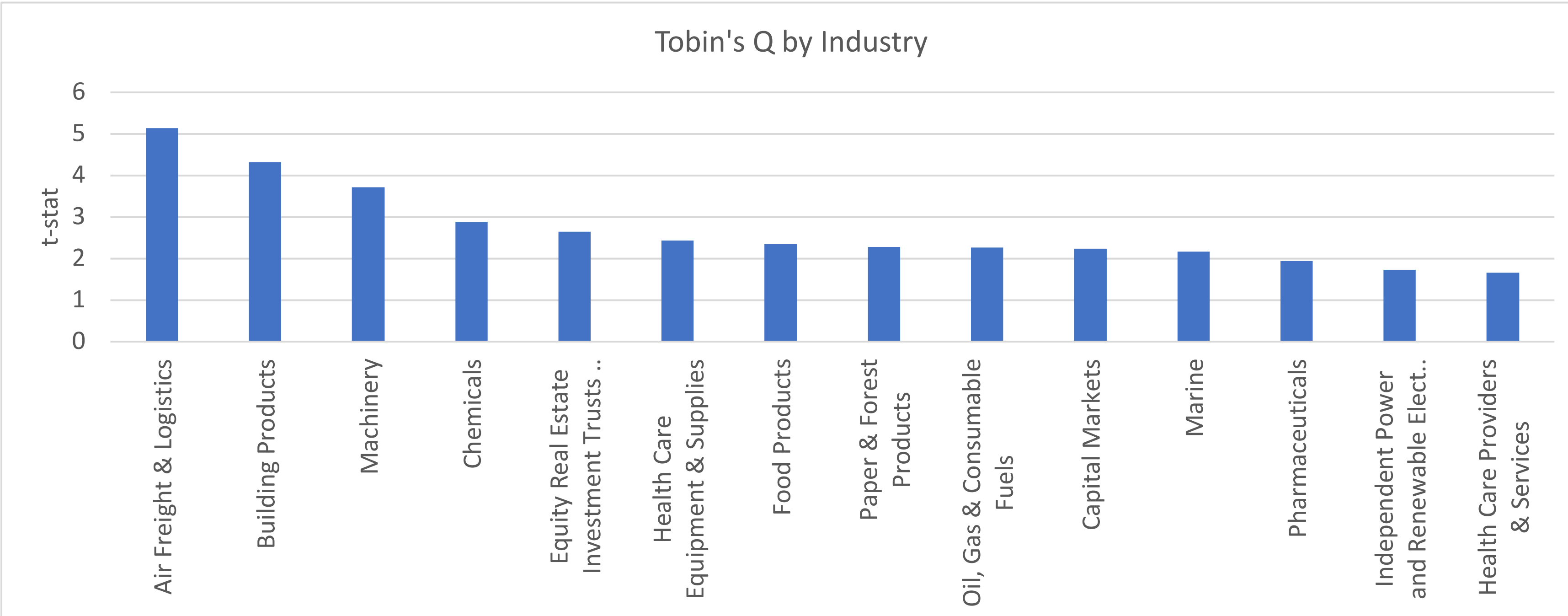


Table 1: Descriptive statistics

	Employment impact	*Wage quality*	*Diversity*	*Opportunity Across Job Categories*	*Opportunity Across Seniorities*	*Location*
N	22,322	22,322	22,322	22,322	22,322	22,322
Mean	$ 545,000,000	$ 695,000,000	$ (173,000,000)	$ (3,033,853)	$ (8,786,529)	$ 34,900,000
Median	$ 82,000,000	$ 120,000,000	$ (37,000,000)	$ (668,867)	$ (2,589,744)	$ 5,762,064
Standard deviation	$ 1,870,000,000	$ 2,240,000,000	$ 529,000,000	$ 10,300,000	$ 23,400,000	$ 117,000,000
Minimum	$ (1,841,285)	$ 71,005	$ (14,800,000,000)	$ (318,000,000)	$ (593,000,000)	$ 3,361
Maximum	$ 40,200,000,000	$ 44,900,000,000	$ (43,112)	$ -	$ -	$ 2,470,000,000

Table 2: Sources of variation in employment impact intensity

	+ Year effects	+ Industry effects	+ Subindustry effects
Ln(Employment intensity)	27.46%	44.31%	48.38%

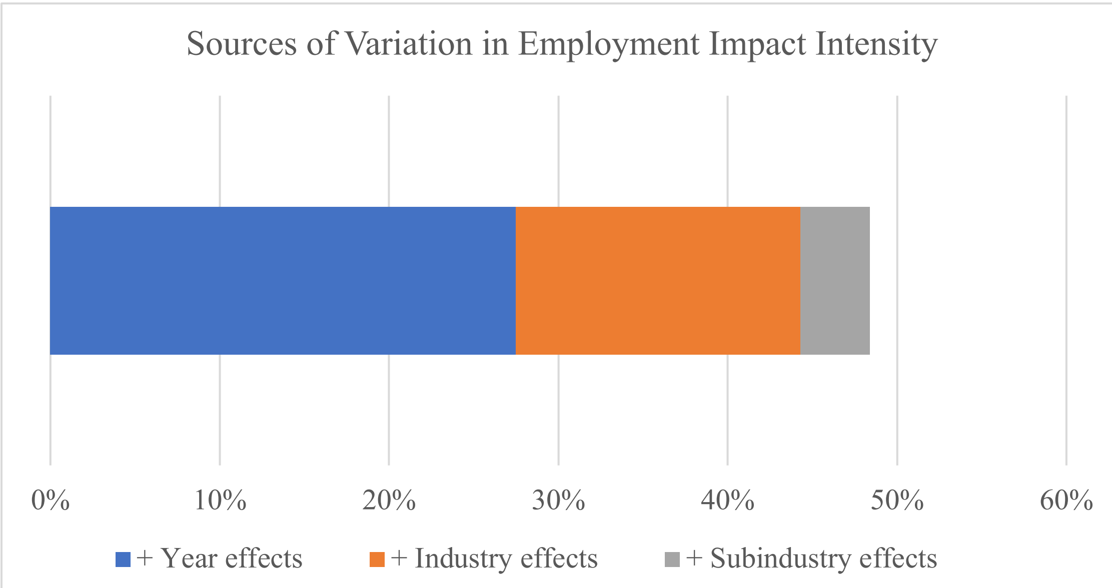


Table 3: Employment impact intensity and financial characteristics

	(1)	(2)	(3)
VARIABLES	*Ln(Employment impact)*	*Ln(Employment impact)*	*Ln(Employment impact)*
Return on Assets	0.002	-0.002	-0.001
	(0.81)	(-0.94)	(-0.86)
Leverage	-0.067***	-0.075**	0.021
	(-6.53)	(-2.22)	(0.93)
Capex	-0.778***	-0.736***	0.003
	(-20.28)	(-5.41)	(0.03)
R&D/Sales	0.415***	0.351***	0.212***
	(29.60)	(4.45)	(5.62)
Dividends	-0.045	-0.123	-0.213*
	(-1.38)	(-1.15)	(-1.96)
Sales	0.063***	0.058***	0.070***
	(59.77)	(18.32)	(29.42)
Constant	9.618***	9.726***	9.437***
	(437.76)	(137.27)	(178.01)
Observations	20,512	20,512	20,512
Adjusted R-squared	0.167	0.408	0.554
Year FE	No	Yes	Yes
Industry FE	No	No	Yes

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Correlation among employment impact intensity components

	Ln(Wage quality)	*Ln(Diversity)*	*Ln(Opportunity A)*	*Ln(Opportunity W)*	*Ln(Location)*
Ln(Wage quality)	1				
Ln(Diversity)	0.5215	1			
Ln(Opportunity A)	0.0596	0.0491	1		
Ln(Opportunity W)	0.1454	0.0593	0.3738	1	
Ln(Location)	0.4189	0.3749	0.0044	0.04	1

Table 5: The relation between employment impact intensity and ESG social ratings

		Refinitive		Sustainalytics		MSCI	
Independent variable		Coeff	t stat	Coeff	t stat	Coeff	t stat
Ln(Employment impact)	Across market	0.0030	8.84	0.0027	2.08	0.0024	0.59
	Within industry	0.0030	10.47	0.0033	4.20	0.0050	1.40

Table 6: Employment impact intensity and employee turnover

VARIABLES	(1) Turnover	(2) Inflows	(3) Outflows
Ln(Employment impact)	-0.013*	0.045***	0.032***
	(-1.94)	(4.60)	(4.50)
Leverage	0.015**	-0.021**	-0.006
	(2.01)	(-2.16)	(-0.69)
Capex	-0.320***	0.387***	0.067***
	(-7.88)	(9.24)	(2.75)
R&D/Sales	-0.076***	0.107***	0.032
	(-4.46)	(6.91)	(1.56)
Dividends	0.060***	-0.089***	-0.029
	(2.83)	(-2.97)	(-1.47)
Sales	0.005***	-0.002	0.003***
	(5.48)	(-1.44)	(3.35)
Constant	0.002	-0.275***	-0.273***
	(0.03)	(-2.99)	(-4.20)
Observations	20,534	20,534	20,534
Adjusted R-squared	0.109	0.274	0.278

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Components of employment impact intensity, inflows, outflows, and turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES			turnover					inflows					outflows		
Ln(Wage quality)	-0.021***					0.044***					0.023**				
	(-2.69)					(2.90)					(2.00)				
Ln(Diversity)		-0.011***					-0.006					-0.017**			
		(-2.97)					(-0.73)					(-2.24)			
Ln(Opportunity Across Categories)			0.001*					-0.002					-0.000		
			(1.77)					(-1.61)					(-0.38)		
Ln(Opportunity Across Seniorities)				0.004					-0.003					0.001	
				(1.62)					(-0.84)					(0.48)	
Ln(Location)					-0.014**					0.025**					0.011
					(-2.21)					(2.20)					(1.25)
Constant	0.108	0.003	-0.135***	-0.154***	-0.009	-0.336**	0.216**	0.166***	0.174***	-0.048	-0.228*	0.219**	0.032*	0.020	-0.057
	(1.23)	(0.06)	(-6.96)	(-5.19)	(-0.17)	(-2.04)	(2.36)	(6.27)	(4.56)	(-0.54)	(-1.81)	(2.59)	(1.79)	(0.87)	(-0.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568	20,568
Adjusted R-squared	0.107	0.107	0.106	0.107	0.107	0.266	0.263	0.263	0.263	0.264	0.272	0.274	0.271	0.271	0.271

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Employment impact intensity and firm financial performance

VARIABLES	*Tobin's Q*
Ln(Employment impact)	0.185*
	(1.76)
Leverage	-0.538***
	(-3.19)
Capex	2.935***
	(3.35)
R&D/Sales	1.320**
	(2.52)
Dividends	3.863***
	(3.86)
Sales	-0.021
	(-1.06)
Constant	0.137
	(0.15)
Observations	19,803
Adjusted R-squared	0.303

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Components of employment impact intensity and firm financial performance

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Tobin's Q		
Ln(Wage quality)	0.419***				
	(3.18)				
Ln(Diversity)		0.111			
		(1.42)			
Ln(Opportunity Across Categories)			-0.001		
			(-0.12)		
Ln(Opportunity Across Seniorities)				-0.044**	
				(-2.03)	
Ln(Location)					0.214**
					(2.29)
Constant	-2.727*	0.630	1.890***	2.286***	0.193
	(-1.86)	(0.66)	(5.46)	(7.21)	(0.25)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	19,830	19,830	19,830	19,830	19,830
Adjusted R-squared	0.304	0.303	0.302	0.303	0.303

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Appendix 1: Mapping Employment Intensity Impact Dimensions

Note: mapping is illustrative and not comprehensive.

Impact Dimension	*Sustainable Development Goals*	*SASB Human Capital General Issue Categories*	*Global Reporting Initiative*	*Stakeholder Capitalism Metrics (Core)*	*GIIN IRIS+*
Wage Quality	*SDG 1: No poverty* *SDG 2: Zero hunger*	*Labor Practices, Employee Diversity, Inclusion, and Engagement*	*GRI 102.8: total number of employees by type, gender* *GRI 202-1 Ratios of standard entry level wage by gender compared to minimum wage*	*Wage Level: Ratios of standard entry-level wage by gender compared to local minimum wage* *Direct economic value generated and distributed (employee wages and benefits)*	*Average Non-Salaried Wage (OI8791), Employees: Minimum Wage (OI5858), Temporary Employee Wages (OI4202)* *'Gender Wage Equity (OI1855), Wage Equity (OI1582), Wage Premium (OI9767)*
Opportunity	*SDG 5: Gender Equality* *SDG 10: Reduced Inequalities*	*Employee Diversity, Inclusion, and Engagement*	*GRI 406: Non-discrimination* *GRI 202-2: Proportion of senior management hired from local community* *GRI 405-2: Ratio of salary and remuneration to women & men*	*Ratio of the basic salary and remuneration for each employee category by significant locations of operation for priority areas of equality: women to men; minor to major ethnic groups; and other relevant equality areas*	*Full-time Employees: Female Managers (OI1571), Full-time Employees: Managers with Disabilities (OI8292), Full-time Employees: Minorities/Previously Excluded Managers (OI3140, Investment Committee Members: Female (OI8709)*
Diversity	*SDG 5: Gender Equality* *SDG 10: Reduced Inequalities*	*Employee Diversity, Inclusion, and Engagement*	*GRI 405-1: Diversity of (governance bodies and) employees*	*Percentage of employees per employee category, per age group, gender, and other indicators of diversity (e.g., ethnicity)*	*Full-time Employees: Female (OI6213), Full-time Employees: Minorities/Previously Excluded (OI8147)*
Location	*SDG 8: Decent work and economic growth*	Labor Practices	*GRI 102-7.1.2.3.3: total number of employees by country or region*	*Absolute number and rate of employment*	*Permanent Employees: Low-Income Areas (OI8266)*

Sources:
https://www.un.org/sustainabledevelopment/sustainable-development-goals/ https://sasb.materiality.org
https://www.weforum.org/stakeholdercapitalism https://www.globalreporting.org/standards/gri-standards-download-center/ https://iris.thegiin.org/metrics/

Appendix 2: Data Dictionary from Revelio Labs

Information provided directly from Revelio Labs.

The underlying data to create Revelio's workforce dataset is collected from unstructured online public profiles, resumes, and job postings. The Revelio Labs dataset curates and structures this data, through the use of proprietary algorithms, and provides employee counts, inflows, and outflows which can be analyzed by positions, skills, geographies, and seniority levels over time.

A. Relevant Variables and Descriptions

company
Categorical
Name of the company

count
Float
The expectation of the number of employees in the position represented in that row at that date

inflow
Float
The expectation of the number of employees moving into the position specified at that month

outflow
Float
The expectation of the number of employees moving out of position specified at that month

month
Time
The month and year of the position. Headcount uses whether an employee was working in that position at any point during the month. Inflows and outflows use the month of the employee's start date and end date, respectively.

salary
Float
The expectation of the *total* salary for employees in the position represented in the row at that date (corresponding to count). Revelio predicts the salary for each position based on role, seniority, company, and country. Revelio trains this model using over 50 million salaries and gets an out-of-sample root mean squared error (RMSE) of 8%.

job_category
Categorical
Job role, where there are 8 unique job categories: administrative, engineer, finance, management, marketing, sales, scientist, and technician. The job category taxonomy is developed by Revelio's proprietary representation and clustering algorithms. Revelio develops mathematical

representations of each job title using the title itself and the text description of the position, either by individuals describing their own experiences or by employers in a job posting. The clustering algorithm is in the family of hierarchical/agglomerative clustering algorithms. The algorithm begins with every job title occupying its own cluster, then iteratively combining clusters based on a set of criteria. Revelio updates this taxonomy periodically to adjust to the changing occupational landscape.

location
Categorical
Metropolitan Statistical Area (MSA)

seniority
Ordinal
The level of seniority of a position, where there are 4 possible values: 1, 2, 3, and 4. The most junior level is 1 and the most senior level is 4. The seniority model, by design, is based on the expected seniority of the title, accounting for industry and company size. Age and tenure do not directly determine seniority. If there are two people with identical titles in the same industry in companies of the same size, those people in their position would get the same seniority score even if they had very different lengths of time in the workforce.

gender
Categorical
The estimated gender, based on the first names of employees. The probabilities for names are derived from the US social security administration.

race and/or ethnicity
Categorical
The estimated race and/or ethnicity, based on the first and last names of employees. The probabilities for names are derived from US voter registration data. The four categories used are Asian, Hispanic, Non-Hispanic Black, and Non-Hispanic White. The four categories were chosen based on the Revelio model's capacity to accurately predict ethnicity and/or race based on voter registration records. Categories with smaller recorded populations (e.g., Native Hawaiian or Other Pacific Islander) lack substantial voter registration records and therefore cannot be accurately predicted using Revelio's current model. Additional information on the model used for this variable is available here: https://ethnicolr.readthedocs.io/

B. Advanced Methodology Descriptions

Weighting

The raw data analyzed is a non-random sample of a company's population. To generate data that is representative of the true underlying population of interest, Revelio employs sampling techniques based on the representativeness of the different groups that we observe. The variables used to stratify these estimates are *occupation* and *country*.

Lags
It takes some time for the data to be updated both from the collection from the web and also from individuals who may delay the rate at which they update their online professional profiles. This introduces a systematic underrepresentation of the rate at which people transition in the very recent past, relative to the distant past. To adjust for this, Revelio employs sampling methods to adjust for this pattern so that they can always provide an unbiased estimate of the flows of employees at every time period.

Identical Titles in Different Industries
Revelio data represents different jobs at the job title and industry level. It is not uncommon for identical titles to represent fundamentally different occupations when they are used in different industries. For example, an associate at an investment bank will fundamentally differ from an associate at a law firm. Revelio allows the machine to decide whether the same titles should be in the same cluster across different industries – if they are similar in their descriptions, they will be; if not, they will be in different clusters.

Uniformity of Clusters
Today's standard clustering algorithms are extremely poor at deriving uniformly sized groups. In order to derive a set of clusters that could be used as a universal occupational taxonomy, Revelio developed a proprietary clustering algorithm that can overcome this limitation.

Uncommon Titles
Although Revelio trains mathematical representations of job titles based on their text descriptions, the algorithm can assign representations to all titles, even if they have never shown up before in Revelio's sample and do not have any text descriptions. This is done through character and substring matching to the titles that Revelio has well-trained representations for. This allows Revelio to classify every single position, no matter how uncommon. There will not be another category in the Revelio Labs taxonomy unless the title of a position is completely missing.

Appendix 3: Marginal Impact of Income

Drawing on research that suggests the marginal utility of income decreases as income increases (Layard et al., 2008; Jebb et al., 2018; Diener et al., 1993) and previous efforts to create a marginal utility function for income (Vionnet and Haut, 2018), we design a function to convert raw salaries into impact values at a marginally decreasing rate. The function is underpinned by two key principles: first, the functional form of the marginal rate, which should show accelerating reduction of the marginal utility of an additional dollar of wages for higher level of wages and, second, identification of an inflection point at which a raw wage should begin to reflect decreasing marginal returns. While we strive to design a functional form and identify an inflection point based on a broadly applicable methodology that is aligned with research on the marginal utility of income, more research is needed to empirically test the nature of the income-impact relationship. Such research could guide applications of the measurement of wage quality.

Functional Form[21]

We design a function such that the marginal rate takes a negative exponential functional form. Therefore, the curve that describes the adjusted salaries is a natural logarithm. Exhibit A1 provides a visual representation of each function. The inclusion of the marginal impact of income function to our framework provides a method for distinguishing between a firm that pays 10 employees each $10,000,000 in salaries and a firm that pays 1,000 employees each $100,000 in salaries (both pay $100,000,000 in total salaries). The use of a negative exponential function to describe the marginal rate allows for a conservative approach to adjusting salaries above, but close to, the designated inflection point (discussed below). We use an elasticity measure of 1.26 to calculate the marginal utility of income, based on Layard et al.'s analysis of six surveys across multiple geographies, in which no systematic differences were found based on sex, age, education, or marital status (Layard et al, 2008). Exhibit A1, Marginal Rate, begins at $120,000 and shows the marginal rate declines to .4 when the raw salary reaches $250,000. This translates into a salary of $250,000 being adjusted down by approximately $50,000, as shown in Table 23. Continuing the declining marginal utility function, a raw salary of $1,000,000 is reduced to a positive impact of $315,127 at a marginal rate of .07.

Inflection Point

Jebb et al. (2018) identify the income satiation level for life evaluation as $105,000 on average for North America. We use this value as the inflection point at which the marginal impact of incomes begins decreasing. However, just as the living wage varies across geographies, this average level of income satiation likely varies across geographies. According to the MIT living wage calculator, the average living wage in the US for a family of four (two children, two working adults) is $34,403. We calculate the average living wage for Intel employees to be $39,880, approximately 16% above the national average. To incorporate a contextual measure of location into the inflection point, we increase the average income satiation by 16%, moving from $105,000 to approximately $121,714. Based on the regional income satiation values in the Jebb et al analysis, as well as the availability of living wage estimates in other geographies, we can replicate this location-based adjustment in future analyses. Table 23 describes the marginal rate and approximate adjusted salary for intervals of $10,000.

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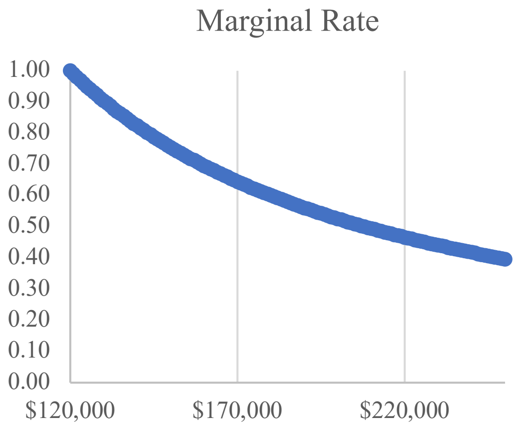
[21] The authors recognize Ben Lawton, of KKS Advisors, for his significant contribution designing and testing the functional form of the marginal utility of income methodology.

Exhibit A1: Marginal Rate and Raw and Utility-Adjusted Salaries



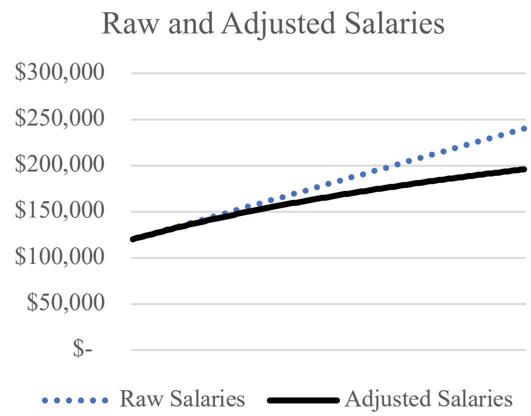


Table 23: Utility-Adjusted Salaries

Raw Salary	Marginal Rate	Adjusted Salary
$100,000	1	$100,000
$110,000	1	$110,000
$120,000	1	$120,000
$130,000	0.904	$129,506
$140,000	0.823	$138,132
$150,000	0.755	$146,015
$160,000	0.696	$153,262
$170,000	0.645	$159,960
$180,000	0.600	$166,179
$190,000	0.560	$171,977
$200,000	0.525	$177,403
$210,000	0.494	$182,497
$220,000	0.466	$187,294
$230,000	0.441	$191,825
$240,000	0.418	$196,113
$250,000	0.397	$200,182