Crushing the Competition: the Pro-Competitive Effects of Relative Performance Evaluation

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Abstract

Relative Performance Evaluation (RPE) is a feature of executive compensation that evaluates a manager's performance relative to peer firms. Economic theory predicts that, under sufficient risk sharing between managers and shareholders, firms that adopt RPE should engage in more aggressive product-market conduct (i.e. charge lower prices). However, the extent of RPE adoption and its market effects remain disputed: firm disclosures often reference RPE, yet managers' pay shows little correlation with competitors' performance despite its well-documented sensitivity to market-wide shocks. We study the adoption and product-market effects of RPE using a network oligopoly model (Pellegrino, 2025) with ultra-realistic managerial incentives, disciplined by granular data from over 350,000 executive compensation contracts. We find that RPE is widespread in form but limited in substance: pay remains tied mainly to absolute objectives, and relative performance is typically benchmarked against broad stock-market indices rather than close rivals. These adoption patterns substantially dampen RPE's competitive impact, reconciling the seemingly contradictory evidence. Counterfactual simulations indicate that stronger, rival-based RPE could enhance competition and consumer welfare, but such effects remain modest under current practices.

JEL Codes: D2, D4, D6, E2, L1, L2, M1, M5, O4

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1 Introduction

Relative Performance Evaluation (RPE) is a well-known feature of executive compensation contracts. It ties executives' pay to a firm's *relative performance* against a peer group, rather than to its *absolute performance*. The primary goal of RPE, supported by the theory of optimal contracts (Holmstrom, 1982; Murphy, 1999), is to filter out common shocks and better align managerial incentives with shareholder interests.

Beyond its implications for contracting efficiency, RPE may also shape real economic outcomes. When considered in the context of oligopolistic competition, RPE is predicted to alter the product market conduct of adopting firms. The economic intuition is that when managers are rewarded for outperforming their competitors, their incentives shift from maximizing their own firm's profits to undercutting those of their peers (Aggarwal and Samwick, 1999). Theory therefore predicts that the adoption of RPE should lead to more aggressive pricing and more intense product market competition. This behavior can reduce industry profits while benefiting consumers through lower prices and greater allocative efficiency. These pro-competitive effects have remained relatively understudied until recently, due to the limited availability of detailed data on executive contracts (Gong et al., 2011; De Angelis and Grinstein, 2011).

The extent of RPE adoption and its product market consequences remain disputed. As summarized by Edmans, Gabaix, and Jenter (2017) in their review of the literature, filings of publicly-listed firms suggest that RPE is a standard feature of executive pay packages, particularly among large firms (Faulkender and Yang, 2010, 2013; Gong et al., 2011; Lewellen, 2015; Bettis et al., 2018). Yet the empirical literature finds that executive pay is largely disconnected from competitors' performance and instead correlates with broader industry outcomes (Albuquerque, 2009; Jayaraman et al., 2021). At the same time, new evidence based on recently available compensation data suggests at least some evidence of product market effects (see Bloomfield et al., 2022; Bloomfield, 2023; Feichter et al., 2022). Figure 1 shows that the number of publicly listed firms using RPE in executive pay rose from fewer than 200 in 2006 to over 550 by 2017, consistent with the upward trend documented in this literature.

The aim of this paper is to reconcile the contrasting evidence produced by the literature so far and to provide a quantitative analysis of the implications of RPE adoption for product markets and economic aggregates. We study how RPE affects firm profitability, consumer surplus, prices, and output by combining rich data on executive compensation contracts with a large-scale oligopoly model.

On the data side, we process unstructured data on more than 350,000 executive compensation contracts from ISS IncentiveLab to extract detailed information on performance-based incentives, including the presence of relative versus absolute performance measures, contract duration, performance metrics, and peer composition. This granularity enables us to translate complex, multi-objective contracts into measures of managerial pay sensitivity to competitors' profits. The resulting dataset takes the form of a weighted network, where firms are represented by nodes and edges capture RPE relationships, specifically, the negative weight that a firm places on each competitor's profits. Within our model, both this RPE network and its overlap with the underlying network of product-market rivalries are key determinants of the pro-competitive effects of RPE.

To quantify the product market effects of RPE, we build a large-scale oligopoly model with ultra-realistic managerial incentives. The framework is a generalization of the network oligopoly model of Pellegrino (2025), enabling us to study competition among publicly listed U.S. firms at scale, and to measure product substitution in a data-driven way using the product-similarity measures of Hoberg and Phillips (2016). The model features a flexible specification of each firm's objective function, obtained from the linear aggregation of goals specified in its managers' compensation contracts. There are four layers of aggregation: we begin with individual goals, which combine to form contracts; contracts are then aggregated to the manager level; and by further aggregating across managers within the same firm, we obtain the firm-level objective func-

Figure 1: RPE Active Contracts 2006-2021

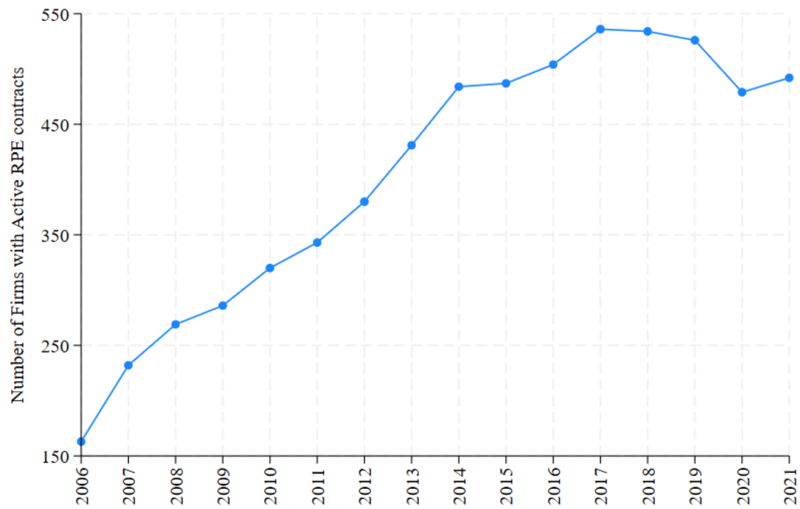


FIGURE NOTES: The lineplot describes the evolution of the number of U.S. publicly listed companies featuring active RPE contracts in a given year. The time period ranges from 2006 and 2021. The source of the data is the ISS Incentive Lab.

tion. This structure closely mirrors that of the IncentiveLab data and makes it possible to use the derived RPE network to structurally parameterize each firm's objective function, which depends on both absolute and relative performance objectives and shapes the firm's competitive behavior.

Analytically, the tractability of the GHL framework allows us to solve for the Nash-Cournot equilibrium of the generalized oligopoly model in closed form. We then conduct counterfactual analyses to quantify the effects of RPE on firm prices, output, and profitability, as well as its implications for consumer surplus.

Our analysis yields several key findings. First, we examine the degree of product market overlap between RPE peers. We find that product similarity, as measured by Hoberg and Phillips (2016), is positively correlated with the magnitude of the (negative) weights that focal firms assign to peers in their RPE contracts. In other words, firms tend to place stronger negative weights on competitors that produce similar goods, suggesting that RPE incentives may encourage firms to undercut close rivals in product market competition. However, a substantial number of firms do not explicitly benchmark their performance against direct competitors.

Second, we document substantial heterogeneity in peer-group selection for RPE adoption. While the use of RPE has become widespread, many firms benchmark their performance against broad market indices such as the S&P 500 or Russell 2000, rather than against narrowly defined sets of direct competitors. These Index-based RPE contracts reflect overall market performance but often include many firms that are not directly related to the focal firm, weakening RPE's competitive impact on product markets (Bloomfield, 2023). In contrast, we define Strict RPE as contracts in which firms benchmark against a carefully selected set of direct competitors. Strict RPE groups are smaller and more targeted than Index-based ones, and their adoption is associated with more aggressive pricing and quantity strategies, consistent with Bizjak et al. (2022) and Feichter et al. (2022).

Third, our granular dataset allows us to study both the extensive and intensive margins of RPE adoption. The extensive margin captures the share of firms incorporating RPE into contracts, while the intensive margin measures the weight placed on RPE, particularly Strict RPE, relative to absolute performance evaluation. We document that among firms with active RPE contracts in 2021, roughly 40% rely exclusively on Index-based RPE, and 25% allocate a positive but small share (less than 20%) of their contract value to Strict RPE. The relatively low weight placed on Strict RPE at the intensive margin helps explain the limited effect of RPE on product market competition.

Finally, we assess the welfare implications of RPE adoption by comparing observed outcomes with a counterfactual world without RPE. Under current adoption patterns, total welfare rises modestly (~0.05% annually), driven by consumer-surplus gains (+0.1%) that offset declines in corporate profits (−0.1%). Counterfactual scenarios in which firms place greater emphasis on relative performance objectives produce roughly twice the welfare gains (~0.1%), highlighting the limited real-world impact of current RPE intensity. Welfare improvements stem primarily from increased output and lower markups, particularly among Strict RPE adopters. However, because larger firms dominate RPE adoption, their more aggressive strategies disproportionately reduce the profits of smaller, non-RPE firms.

Our paper contributes to several strands of literature. First, our work builds on recent literature in modeling oligopolistic competition with Generalized Hedonic Linear (GHL) demand (Pellegrino, 2025; Ederer and Pellegrino, 2025). These studies use text-based product similarity data to quantify market power and welfare effects in differentiated product markets. We extend this framework by incorporating managerial incentives shaped by executive compensation contracts, which enables analysis of how strategic interactions evolve under RPE.

Second, we contribute to the literature on executive compensation, which documents both its dramatic growth (Gabaix and Landier, 2008; Edmans et al., 2017) and its influence on firm behavior (Kim and Lu, 2011; Cziraki and Groen-Xu, 2020). Shi (2023) examines the role of noncompete clauses using executive pay data, and Chemla et al. (2025) develop a dynamic general equilibrium model of executive compensation with moral hazard, showing that firms' compensation choices create externalities by affecting executives' outside options. Complementing this literature, our findings emphasize the importance of the interaction between managerial incentives and market structure, and we analyze how compensation design shapes firm performance. Moreover, our study advances empirical work on RPE adoption (Aggarwal and Samwick, 1999; Albuquerque, 2009; Bettis et al., 2018) and its competitive implications. We reconcile theoretical predictions of RPE-induced "sabotage" (Feichter et al., 2022; Bloomfield, 2023), which posit that relative-performance incentives can intensify competition by rewarding managers for actions that harm their peers, such as price undercutting or product imitation[1], with empirical evidence of muted aggregate effects (Jayaraman et al., 2021). These findings show that outcomes depend critically on the alignment between benchmarking networks and product-market rivalries, and that competitive aggressiveness is amplified when peer relationships are reciprocal.

Third, our work relates to the growing macroeconomic literature on market power (De Loecker et al., 2020; De Loecker and Eeckhout, 2018; Syverson, 2019; Autor et al., 2020; Döpper et al., 2022). We contribute by exploring how executive compensation, in particular RPE, influences competitive behavior and market power. Bao et al. (2023) also study interactions between market structure and managerial incentives, but in contrast we treat RPE adoption as the source of competitive dynamics rather than as a response to exogenous market power. Our findings suggest that RPE can mitigate market power by encouraging more aggressive competition, especially when firms benchmark against specific peers.

Fourth, we connect to the literature on performance pay and relative performance evaluation in personnel economics (Lazear and Rosen, 1981; Lazear, 2000). RPE is typically implemented within firms to evaluate and incentivize workers' effort. For top executives, however, peer groups within a firm are difficult to define, so firms design contracts that compare their own performance with that of external peers. We study how

[1]In our quantitative analysis, however, product differentiation is treated as exogenous and the competitive effects operate through quantity (price) competition.

this use of RPE transmits incentives across firms and alters product-market competition.

Finally, our paper relates to the macroeconomic networks literature (Acemoglu et al., 2012; Carvalho, 2014; Acemoglu et al., 2017; Carvalho and Tahbaz-Salehi, 2019; Baqaee and Farhi, 2020; Liu and Tsyvinski, 2020; Pereira Marques de Carvalho et al., 2021; Carvalho et al., 2020), which analyzes how input-output linkages propagate idiosyncratic shocks. While prior work focuses mostly on production networks, we instead model two distinct networks: one capturing product market rivalries and another reflecting RPE benchmarking relationships. Methodologically, we also build on the literature on linear-quadratic network games (Ballester et al., 2006; Galeotti et al., 2020) and potential games (Monderer and Shapley, 1996). Our framework generalizes these models to incorporate RPE incentives into product market interactions.

In summary, this paper bridges the gap between theory and empirics by offering a comprehensive analysis of the product-market implications of RPE adoption. We show that although RPE has the potential to enhance competition and improve welfare, its impact depends critically on how it is adopted and on the alignment between benchmarking relationships and product-market rivalries. As the use of RPE continues to expand, understanding these mechanisms is essential for firms and policymakers aiming to foster competitive markets and promote consumer welfare.

The remainder of the paper is structured as follows. Section 2 describes the data sources and methodology. Section 3 presents the theoretical framework, including the GHL demand system and the model of managerial incentives. Section 4 develops the empirical implementation of the model, including the construction of relative performance metrics and other inputs, the solution of equilibrium quantities, and several validation checks. Section 5 reports the empirical findings, documenting the time trends in RPE adoption and its effects on product market outcomes. Section 6 concludes and discusses the implications of our findings for both theory and policy.

2 Data

This section describes the data sources used in our analysis and the key variables relevant for model estimation and identification. Section 4 explains in detail how these data are incorporated into the quantitative model.

2.1 Executive Compensation Data

To estimate our model, we must obtain detailed information on executive compensation contracts and their structure. To this end, we leverage data from the Institutional Shareholder Services (ISS) IncentiveLab, accessed via Wharton Research Data Services (WRDS) platform. Following SEC disclosure requirements, U.S. public firms must report compensation for their three highest-paid executives in proxy statements. We focus on the period 2006-2021, during which reporting standards are consistent.

2.1.1 Hierarchical Structure of the IncentiveLab Data

The ISS IncentiveLab database provides a detailed and structured view of executive compensation practices among publicly listed firms. The data have a hierarchical structure that captures the different levels at which compensation decisions are made and performance incentives are defined. Understanding this structure is essential for interpreting the contractual data and for linking each element of the hierarchy to corresponding components in our quantitative model.

At the top of the hierarchy are firms, each representing a publicly listed company that designs and grants incentive contracts to its executives. Each firm employs a number of managers (or executives), who occupy positions with decision-making authority such as C-suite officers and vice presidents. These managers are the primary recipients of incentive contracts and the agents through whom firms implement strategic objectives. [2]

Each contract between a firm and an executive is recorded in the data as a *grant*, potentially resulting in an *award*. A grant specifies the conditions under which the award vests, either fully, partially, or not at all, through the achievement of one or more performance *goals*, consistent with the hierarchical structure described here. These goals fall into two broad categories: *performance-based* and *time-based*. Performance-based goals evaluate achievement against quantitative metrics such as earnings per share, return on assets, or total shareholder return, and define a payout function that increases with performance. Time-based goals, by contrast, simply require continued employment over a specified period. Our analysis focuses on contracts with performance-based goals, which dominate the ISS IncentiveLab dataset and that directly map to the incentive structure represented in our model.

Goals represent the most granular layer of the hierarchy and specify the precise performance metrics used to determine vesting. In the IncentiveLab data, goals are classified as *Absolute* or *Relative*. Under absolute goals, achievement is measured against predetermined numerical thresholds that are explicitly specified in the contract, such as a target return on equity or earnings-per-share level. By contrast, relative goals evaluate firm performance in comparison to a designated *peer group* of companies, meaning that the executive's compensation depends not only on their own firm's performance but also on its standing relative to competitors. These relative goals create benchmarking links between firms and form the empirical foundation of the Relative Performance Evaluation (RPE) network we analyze.

Between 2006 and 2021, the dataset contains approximately 650,000 absolute goals and 77,000 relative goals, accounting for roughly 90% and 10% of all performance-based goals, respectively. Among the firms in our sample, 1,196 adopt incentive plans that include at least one relative goal, and 678 firms do so when focusing on grants that exclude absolute goals.

These design features of goals determine how performance metrics are defined and evaluated, and they underpin the contractual mechanisms that link firm outcomes to managerial pay. The next subsection explains how these goals are combined within contracts, how their monetary values are computed, and how the overall structure of executive compensation is represented in the data.

2.1.2 Executive Contract Design

As discussed, executive contracts feature uncertain outcomes. In this section, we describe their structure and explain how we compute their expected monetary value. Attaching a dollar value to each contract is essential because it allows us to determine the relative weights across the contracts held by a given manager and, in turn, the manager's overall value to the firm. These relative weights then allow us to infer how much importance firms place on the performance of other firms when making production and compensation decisions.

Executive contracts link payouts to performance througha a payout schedule that is increasing in performance. Each contract defines three performance thresholds - *Threshold*, *Target*, and *Max* - in ascending order of difficulty[3]. All payments are expressed relative to the Target level and follow a piecewise linear schedule. If performance falls below *Threshold*, the executive receives no payment. Reaching *Threshold* triggers a partial payout, typically a fixed fraction of the Target award. Achieving *Target* yields the full Target

[2] An executive may sit on the board of multiple firms. Yet, after a thorough inspection it does not seem interlocking is an important driver of firms' interaction on the product markets. This is due to the fact that interlocking of executives is not well received from the regulator. It is instead common practice that *independent directors* sit on multiple boards. However, they do not have direct influence on the operations of the firms nor is their compensation performance-based which makes their impact hard to measure.

[3] Each payout level requires the firm to outperform a larger mass of firms in the distribution of performance. Further discussion on this follows in Section 4.

payment, while reaching *Max* results in a payout that is a multiple of the Target amount. This structure applies to both absolute and relative goals.

For equity-based awards, ISS IncentiveLab reports the fair value at grant date. For non-equity awards, we impute the fair value by combining ISS threshold payment terms with probability estimates from Compensation Advisory Partners. These probabilities apply uniformly across goal types within contracts[4]. Let t index the four regions of performance defined by the contract thresholds: below *Threshold*, between *Threshold* and *Target*, between *Target* and *Max*, and above *Max*. For each region t, $B_k(t)$ denotes the conditional expected payout within that region. The fair value of a generic contract k is computed as the weighted sum of the payments across the possible levels of achievement:

$$\text{FairValue}_k = \sum_t p(t) B_k(t), \tag{2.1}$$

where $p(t)$ is the probability of reaching region $t \in \{BelowThreshold, Threshold, Target, Max\}$, and $B_k(t)$ is the corresponding payout.

2.1.3 RPE types and Peers Data

Relative goals require identifying a peer group. We observe two main modes of RPE. Under Strict RPE, firms explicitly list peer firms by name. Under Index-based RPE, firms benchmark performance against a pre-specified equity index (e.g., the S&P 500 or Russell 2000) or an industry subset (e.g., S&P 500 Consumer Staples). ISS Incentive Lab reports the composition of peer groups only for Strict RPE contracts. For Index-based RPE, it reports the index name but not its constituents. We reconstruct the missing information using two complementary data sources. For 2006-2010, we compile index constituents for eight major indices (S&P 500, S&P 400, S&P 1500, S&P 600, Nasdaq 100, Dow Jones, Russell 2000, and Russell 3000) from Global Financial Data Finaeon and combine them with Compustat data to construct industry-level indices following the four-tier Global Industry Classification Standard (Sector, Industry Group, Industry, and Sub-Industry). For 2011-2021, we use proprietary historical constituent data for the S&P 500, S&P 400, S&P 600, and S&P Total Market Index, provided by Standard & Poor's Dow Jones Indices.

3 Structural Model

To study the interaction between RPE and product market competition, we extend the network oligopoly model of Pellegrino (2025) by introducing realistic executive incentives that can be disciplined by the IncentiveLab data.

3.1 Consumer Demand and Production

We embed managerial incentives into a differentiated product economy built on a generalized hedonic-linear (GHL) demand framework of Pellegrino (2025). This environment provides a flexible yet tractable representation of product differentiation, offering a natural setting to study how performance-based pay and relative evaluation reshape firms' strategic interactions and competitive behavior.

Product representation. A representative household consumes a set of differentiated products indexed by $i \in \{1, 2, ..., I\}$, and derives utility from the characteristics embodied in them. We distinguish two types of characteristics. Common characteristics are dimensions shared across all products, while idiosyncratic

[4]There is no available information about the probability of achievement by goal type. As a consequence we use available probability estimates that the whole set of goals in a contract is achieved.

characteristics are product-specific. Each product i is represented by an N-dimensional vector of observable common attributes normalized to unit length[5]:

$$\mathbf{a}_i = \begin{bmatrix} a_{1i} & a_{2i} & \dots & a_{Ni} \end{bmatrix}' \qquad \sum_{n=1}^{N} a_{ni}^2 = 1 \tag{3.1}$$

The similarity between any two products i and j is measured by the cosine of the angle between their attribute vectors, $\mathbf{a}_i'\mathbf{a}_j \in [0, 1]$, which captures the degree of substitutability in consumers' valuation space. Combining all the product-specific vectors $\mathbf{a}_i$, we obtain an $N \times I$ matrix $\mathbf{A}$:

$$\mathbf{A} \equiv \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_I \end{bmatrix} \equiv \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1I} \\ a_{21} & a_{22} & \cdots & a_{2I} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NI} \end{bmatrix}. \tag{3.2}$$

The gram matrix $\mathbf{A}'\mathbf{A}$ then summarizes the pairwise proximity among goods and defines the product network that maps the degree to which products share common characteristics.

In equilibrium, the representative agent acts both as consumer and producer. Each differentiated product i is produced and consumed in quantity q_i. Collecting these quantities yields the I-dimensional vector $\mathbf{q} = \begin{bmatrix} q_1 & q_2 & \cdots & q_I \end{bmatrix}'$. Let x_n denote the total amount of common characteristic n embodied in aggregate consumption. It is given by

$$x_n = \sum_{i=1}^{I} a_{ni}\, q_i \qquad \text{or (equivalently)} \qquad \mathbf{x} = \mathbf{A}\mathbf{q} \tag{3.3}$$

Consumer preferences and product demand. Let y_i be the amount of the idiosyncratic characteristic associated with product i. Because each unit of good i delivers exactly one unit of its idiosyncratic characteristic, we have $y_i = q_i$.

The representative agent's utility function is quadratic in both the vector of common characteristics ($\mathbf{x}$) and idiosyncratic characteristics ($\mathbf{y}$) and features linear disutility from labor supply (H):

$$U(\mathbf{x}, \mathbf{y}, H) \overset{\text{def}}{=} \alpha \cdot \sum_{n=1}^{N} \left(b_n^x x_n - \frac{1}{2} x_n^2 \right) + (1 - \alpha) \sum_{i=1}^{I} \left(b_i^y y_i - \frac{1}{2} y_i^2 \right) - H \tag{3.4}$$

The parameters b_n^x and b_i^q capture heterogeneity in preferences for each characteristic, while $\alpha \in [0, 1]$ governs the relative weight of common versus idiosyncratic components, and hence the degree of *horizontal differentiation* among products. When $\alpha = 0$, consumers value only idiosyncratic characteristics and each firm behaves as a local monopolist. If $\alpha = 1$, utility depends solely on common characteristics, and competition is maximized through substitutability in the common-characteristic space.

The representative agent chooses the consumption bundle $\mathbf{q}$ taking the vector of prices $\mathbf{p}$ as given. Because she owns all firms, her income consists of labor earnings H and the aggregate profits Π obtained from

[5] The assumption that $\mathbf{a}_i$ has unit length, $\sum_{n=1}^{N} a_{ni}^2 = 1 \quad \forall\, i \in \{1, 2, ..., I\}$, is a scale of product characteristics. The normalization consists in choosing, for each good i, the measurement scale so that i is geometrically represented by a point on the m-dimensional hypersphere. We point the reader to the Appendix of Pellegrino (2025) for a thorough discussion of this normalization.

firm ownership. The budget constraint is therefore

$$H + \Pi \;\geq\; \sum_{i=1}^{I} p_i q_i \tag{3.5}$$

As shown by Pellegrino (2025), the solution to the household optimization problem yields the following inverse demand system:

$$\mathbf{p} \;=\; \mathbf{b} - (\mathbf{I} + \Sigma)\,\mathbf{q} \tag{3.6}$$

where matrix Σ is proportional to the matrix of cosine similarities among products net of its diagonal entries:

$$\Sigma \;\stackrel{\text{def}}{=}\; \alpha\left(\mathbf{A}'\mathbf{A} - \mathbf{I}\right). \tag{3.7}$$

The matrix Σ captures similarity across products. Each off-diagonal elements $\sigma_{ij} \in [0, \alpha]$ reflects how close two products are in their characteristics, and therefore how easily consumers substitute between them. The construction restricts interactions to substitutability rather than complementarity.

The demand intercept vector $\mathbf{b}$ is defined as

$$\mathbf{b} \;\stackrel{\text{def}}{=}\; \alpha\,\mathbf{A}'\mathbf{b}^{x} + (1-\alpha)\,\mathbf{b}^{q} \tag{3.8}$$

Equations (3.6)- (3.8) imply that every firm's output q_i affects the price of all other products (p_j) in this economy. The effect of an additional unit produced by firm j on the price of firm i is $\left(\partial p_i / \partial q_j\right)$ is proportional to $\mathbf{a}_i'\mathbf{a}_j$, the product similarity between i and j. Hence, the closer two products are in the space of common characteristics, the stronger the competitive interaction between their producers.

Production and labor demand. On the production side, each firm i produces output q_i using labor input h_i. Labor is the numeraire, and the wage is normalized to one, so all prices and costs are expressed in units of labor. The total labor required by firm i includes both a fixed component and a variable component proportional to output

$$h_i(q_i) \;=\; d_i + c_i q_i \tag{3.9}$$

The fixed term d_i represents overhead labor requirements that must be paid regardless of production, while c_i captures the per-unit labor need. Aggregate labor demand in the economy is therefore $H = \sum_i h_i$. Fixed costs are treated as sunk but counted in total labor use.

Firms compete à la Cournot, choosing quantities q_i while taking others' outputs as given. Firm i's profit function is

$$\pi_i(\mathbf{q}) \;\stackrel{\text{def}}{=}\; p_i(\mathbf{q})\, q_i - h_i(q_i) \tag{3.10}$$

The cross-price derivative $\partial p_i / \partial q_j$ is proportional to σ_{ij}, the (i, j) entry of matrix Σ. The closer two products are in characteristic space, the larger is σ_{ij} and hence the stronger the competitive pressure between their producers.

Welfare. The linear-quadratic structure of preferences leads to a closed-form expression of welfare. Consumer surplus can be written as the difference between the total utility derived from consumption and the total expenditure on goods:

$$\text{Consumer Surplus} \;=\; \mathbf{q}'(\mathbf{b} - \mathbf{p}) - \frac{1}{2}\mathbf{q}'(\mathbf{I} + \Sigma)\,\mathbf{q}, \tag{3.11}$$

which measures the gap between consumers' total willingness to pay and the expenditure at market prices. Adding consumer surplus to the profits of all firms yields the total surplus:

$$\text{Total Surplus} \quad = \quad \mathbf{q}'\left(\mathbf{b}-\mathbf{c}\right)-\frac{1}{2}\mathbf{q}'\left(\mathbf{I}+\Sigma\right)\mathbf{q}-D, \tag{3.12}$$

where $D=\sum_i d_i$. These expressions show that welfare depends on both the linear benefit-cost component and the curvature of the demand system. The first linear term $\mathbf{q}'\left(\mathbf{b}-\mathbf{c}\right)$ captures the wedge between marginal willingness-to-pay and marginal cost, whereas the quadratic term $-\frac{1}{2}\mathbf{q}'\left(\mathbf{I}+\Sigma\right)\mathbf{q}$ incorporates diminishing marginal utility for each product through the identity component and competitive spillovers across products through the similarity matrix Σ.

3.2 Managerial Incentives

Thus far, the model follows Pellegrino (2025), where firms directly maximize profits. We now extend it by introducing managerial incentives that reflect the contractual structure observed in the ISS IncentiveLab data. In practice, firms delegate strategic decisions to managers whose objectives are shaped by multilayered incentive contracts. These contracts combine absolute and relative performance goals that determine compensation and, in turn, influence firms' competitive behavior in product markets. The model mirrors this hierarchy—goals, contracts, managers, and firms—to align tightly with the IncentiveLab data, allowing us to structurally discipline firm objectives with observed incentive parameters.

The economy consists of I firms run by a total of M *managers*, where naturally $M>I$. Each manager $m\in\{1,2,...,M\}$ is assigned to a firm $i\in\{1,2,...,I\}$. For each firm-manager pair, compensation is determined by one or more contracts indexed by $k\in\{1,2,...,K\}$, where K denotes the total number of contracts in the economy. Each contract specifies performance goals indexed by $g\in\{1,2,...,G\}$, where G is the total number of goals. With slight abuse of notation, we also use I,M,K,G to denote the corresponding sets of firms, managers, contracts, and goals, respectively.

Goals. Each level of the hierarchy contributes to the monetary value of compensation observed in the data. At the goal level, we denote by $r_g\left(\mathbf{q}\right)$ the monetary reward associated with goal g. Although in IncentiveLab the goals are defined in terms of performance metrics, such as earnings per share, return on assets, or total shareholder return, the reward associated with each goal ultimately depends on firm profitability through these metrics. To connect the data to the model, we represent each metric as a linear function of firm profits, introducing a sensitivity parameter β_g that measures how a marginal change in profits affects the goal metric. For instance, a RPE goal based on relative ROA effectively rewards the manager according to the probability that the firm's profit-to-assets ratio exceeds that of a peer firm, which in equilibrium translates into a linear combination of the peer firms' profits. Section 4.1 develops this micro-foundation in detail.

Because some goals evaluate performance relative to peers, the monetary value associated with a given goal r_g may depend on the profits of multiple firms. The focal[6] firm's own profits affect both absolute and relative goals, while the profits of its peers affect only the relative ones. For firms outside the peer group, the corresponding weights are zero.

Formally, we represent each goal's monetary reward as a linear mapping from firm profits:

$$r_g\left(\mathbf{q}\right) \stackrel{\text{def}}{=} \sum_{i=1}^{I} w_{gi}^{r}\,\pi_i\left(\mathbf{q}\right), \tag{3.13}$$

where w_{gi}^{r} is the weight applied to the profits of firm i under goal g. This reward function depends on

[6]In the context of RPE focal refers to the firm who is stipulating the contract. The term is opposed to peer which defines a firm part of the group used to construct the performance benchmark.

the vector of firm outputs $\mathbf{q}$, because each firm's profit$\pi_i(\mathbf{q})$ and, consequently each goal reward $r_g(\mathbf{q})$, are functions of the firms' production and pricing decisions. Stacking all goal weights into a $G\times I$ matrix $\mathbf{W}^r$and all goal rewards into a vector $\mathbf{r}(\mathbf{q})$, we can write compactly:

$$\mathbf{r}(\mathbf{q}) \overset{\text{def}}{=} \mathbf{W}^r \boldsymbol{\pi}(\mathbf{q}). \tag{3.14}$$

The matrix $\mathbf{W}^r$ captures how goal-specific targets transform firm profits into monetary outcomes. In empirical implementation, its elements are disciplined by the estimated sensitivities β_g that map performance metrics into profits (see Section 4.1 for their micro-foundation and identification). Note that $\mathbf{W}^r$ is defined over the economy-wide set of firms and goals, rather than being restricted to a single peer group or industry segment. Each entry is zero whenever the corresponding link is absent in the data. For instance, $w^r_{gi} = 0$ if firm i is not included in goal g. The same convention applies to all subsequent weighting matrices.

Contracts. Each contract aggregates several goals that jointly determine the vesting and payout of a given grant. In the data, these within-grant weights are recorded as *percentVest*, which specifies the fraction of the grant's total value allocated to each goal - recall from Section 2.1.1 the 60/40 split between the two goals in the "{A1+R1}" example. Let $e_k(\mathbf{q})$ denote the monetary value of contract k, which depends on the firm performance vector $\mathbf{q}$ through the goal-level rewards $r_g(\mathbf{q})$. Let w^e_{kg} be the fraction of the contract value assigned to goal g in contract k. The contract-level value is therefore a weighted sum of its constituent goal values:

$$e_k(\mathbf{q}) \overset{\text{def}}{=} \sum_{g=1}^{G} w^e_{kg}\, r_g(\mathbf{q}) \qquad \text{or (equivalently)} \qquad \mathbf{e}(\mathbf{q}) \overset{\text{def}}{=} \mathbf{W}^e \boldsymbol{r}(\mathbf{q}). \tag{3.15}$$

The $K \times G$ matrix $\mathbf{W}^e$ captures how goals are combined within each contract.

Managers. We next define u_m as the total compensation of manager m, which aggregates the monetary values of the contracts she holds. Denote by w^u_{mk} the share of contract k in manager m's total compensation package. The manager-level compensation value is therefore given by

$$u_m(\mathbf{q}) \overset{\text{def}}{=} \sum_{k=1}^{K} w^u_{mk}\, e_k(\mathbf{q}) \qquad \text{or (equivalently)} \qquad \mathbf{u}(\mathbf{q}) \overset{\text{def}}{=} \mathbf{W}^u \mathbf{e}(\mathbf{q}), \tag{3.16}$$

where $\mathbf{W}^u$ is an $M \times K$ matrix collecting all contract weights across managers.

3.3 Firm Objectives and Maximization

We now turn to the firm level and specify how each firm chooses its output under Cournot competition. Each firm i chooses its own output q_i to maximize an objective function $v_i(\mathbf{q})$, which aggregates the utilities of its managers. Let w^v_{im} be the weight of manager m in firm i's objective function. These firm-to-manager weights can be collected in a $I \times M$ matrix $\mathbf{W}^v$. The firm's objective is therefore

$$v_i(\mathbf{q}) \overset{\text{def}}{=} \sum_{m=1}^{M} w^v_{im}\, u_m(\mathbf{q}) \qquad \text{or (equivalently)} \qquad \mathbf{v}(\mathbf{q}) \overset{\text{def}}{=} \mathbf{W}^v \mathbf{u}(\mathbf{q}) \tag{3.17}$$

Our linear specifications imply that the vector of objectives functions $\mathbf{v}(\mathbf{q})$ can be expressed as a linear transformation of firm profit functions:

$$\mathbf{v}(\mathbf{q}) = \mathbf{W}\boldsymbol{\pi}(\mathbf{q}) \qquad \text{where} \qquad \mathbf{W} \overset{\text{def}}{=} \mathbf{W}^v \cdot \mathbf{W}^u \cdot \mathbf{W}^e \cdot \mathbf{W}^r \tag{3.18}$$

Dividing each row i of W by its diagonal entry w_{ii}, we finally can rewrite the objective function of firm

i in relative terms:

$$v_i(\mathbf{q}) \propto \pi_i(\mathbf{q}) + \sum_{j\neq i} \theta_{ij}\,\pi_j(\mathbf{q}) \qquad \text{where} \qquad \theta_{ij} \overset{\text{def}}{=} \frac{w_{ij}}{w_{ii}}. \tag{3.19}$$

The coefficient θ_{ij} measures how much the decision makers of firm i value the profits of firm j relative to their own. Positive values of θ_{ij} indicate that firm i's managers are rewarded for higher profits of competitor j (strategic complementarity), while negative values correspond to relative-performance evaluation (RPE) incentives that reward firm i for outperforming firm j. The matrix $\mathbf{\Theta} = \left[\theta_{ij}\right]$ therefore summarizes the directional strength of RPE links across firms and depends on the four weight matrices $\mathbf{W}^v, \mathbf{W}^u, \mathbf{W}^e$ and $\mathbf{W}^r$. These matrices map individual performance goals into contractual, managerial, and finally firm-level objectives. We shall discuss the empirical measurement of these matrices more in detail in Section 4.

Given this objective, firm i competes à la Cournot to maximize v_i. The first-order condition for optimal output is

$$\frac{\partial v_i}{\partial q_i} = \frac{\partial \pi_i}{\partial q_i} + \sum_{j\neq i} \theta_{ij} \frac{\partial \pi_j}{\partial q_i} = 0. \tag{3.20}$$

This condition shows that firm i's production decision internalizes not only the impact of its own output on its profits but also its effect on the profits of peers to which it is contractually linked through θ_{ij}. When $\theta_{ij} = 0$, firm i values only its own profits (only absolute performance, no RPE). When $\theta_{ij} < 0$, the firm's managers are penalized by the success of peer j, which induces them to expand output or cut prices to outperform their benchmarked peers, and potentially translate into more intense product-market competition. Conversely, $\theta_{ij} > 0$ would imply cooperation or complementarity in objectives, softening competitive pressure, but such links are empirically rare because managerial interlocks across firms seldom occur in executive-level contracts[7].

The matrix Σ, whose entries are proportional to cosine similarities, defines an *undirected network* capturing product-market rivalries, while the matrix $\mathbf{\Theta}$ defines a *directed network* reflecting contractual RPE links. Intuitively, $\Sigma = \Sigma'$ but $\mathbf{\Theta} \neq \mathbf{\Theta}'$. Taken together, they determine how incentive-based interdependence and market structure jointly shape strategic interactions. The Hadamard (entry-by-entry) product $\mathbf{\Theta} \circ \Sigma$ summarizes where contractual benchmarking overlaps with product similarity. Negative entries intensify rivalry by strengthening each firm's perceived gain from expanding output in markets where close competitors are benchmarked against it. In equilibrium, a denser or more negative $\mathbf{\Theta}$ within highly substitutable industries amplifies effective competition, leading to higher aggregate output and lower equilibrium prices.

3.4 Equilibrium and Counterfactual RPE scenarios

We now characterize firms' equilibrium quantities in the aggregate Cournot environment described above. Managers choose their firms' output levels to maximize firm objective function v_i. We model firms' quantity choices as the outcome of a linear-quadratic potential game (Ballester et al., 2006; Monderer and Shapley, 1996). The potential function provides a compact representation of market interactions that accommodates any configuration of incentive links $\mathbf{\Theta}$:

$$\Phi(\mathbf{q}; \mathbf{\Theta}) = \mathbf{q}'(\mathbf{b} - \mathbf{c}) - \tfrac{1}{2}\,\mathbf{q}'(2\mathbf{I} + \Sigma + \mathbf{\Theta} \circ \Sigma)\mathbf{q} - D \tag{3.21}$$

[7] Positive θ_{ij} can arise in two situations. First, it may reflect true interlocking, where a manager holds simultaneous contractual positions in multiple firms, an arrangement that is virtually nonexistent at the executive level. Second, positive values can appear mechanically due to the structure of the IncentiveLab dataset, which is recorded at the grant level. For example, suppose a manager serves at firm A from January 2010 to June 2015 and moves to firm B with a new contract starting in January 2015. Because we conduct analysis at the annual level, the manager would appear to be associated with both firms in 2015, even if the earlier contract effectively terminated. These overlapping grants generate a very small number of positive entries in the empirical $\mathbf{\Theta}$ matrix.

We assume an interior solution which is in line with the observed allocation in which all firms produce strictly positive output. The first order conditions are

$$\mathbf{0} \;=\; \mathbf{b} - \mathbf{c} - (2\mathbf{I} + \Sigma + \mathbf{\Theta} \circ \Sigma)\,\mathbf{q}, \tag{3.22}$$

where $\mathbf{b}$ and $\mathbf{c}$ are the demand and supply function intercepts. Under the assumption that the matrix in brackets is invertible, the equilibrium allocation under RPE incentives, which we call $\mathbf{q}^{\mathrm{RPE}}$, is given by:

$$\mathbf{q}^{\mathrm{RPE}} \;=\; (2\mathbf{I} + \Sigma + \mathbf{\Theta} \circ \Sigma)^{-1}(\mathbf{b} - \mathbf{c}) \tag{3.23}$$

This solution characterizes the observed allocation under the existing RPE network $\mathbf{\Theta}$.

Having characterized the equilibrium under a general incentive structure, we next use this unified representation to construct three counterfactual environments. Each counterfactual modifies the network of incentive weights $\mathbf{\Theta}$ while keeping the product market structure Σ, fundamentals $(\mathbf{b}, \mathbf{c})$, and fixed costs D unchanged.

Cournot (no RPE). To analyze the effects of RPE on firm behaviors and the aggregate economy, we compare the RPE equilibrium to a counterfactual scenario in which firms maximize their own profits π_i as under standard Cournot competition. This is the special case where $\mathbf{\Theta}$ is a null matrix:

$$\mathbf{q}^{\mathrm{Cournot}} \;=\; (2\mathbf{I} + \Sigma)^{-1}(\mathbf{b} - \mathbf{c}) \tag{3.24}$$

Moreover, we construct another two counterfactual scenarios that adjust the weighting of relative versus absolute performance objectives for specific subsets of firms, in order to study the implications of RPE intensity within a firm. These counterfactuals maintain the same market structure as the benchmark RPE case and only affect the matrix of RPE weights, $\mathbf{\Theta}$.

Relative-only counterfactual. This counterfactual applies to all firms whose executive contracts contain any form of RPE in the baseline. In the observed data, these firms typically combine relative goals with absolute goals. Under the Relative-only counterfactual, we set the weights on all absolute (non-relative) goals to zero in any contract that contains at least one RPE. All relative-performance goals, including both strict and index-based, are kept with their baseline proportions and rescaled proportionally to sum to 100% of performance-based pay. Firms that do not use any RPE in the baseline are left unchanged.

Economically, this counterfactual isolates the competitive effects of expanding the role of relative performance for all firms that already rely on RPE, without altering the structure of their peer groups or the composition of relative goals across strict and index-based benchmarks. The adjustment yields a new matrix of RPE weights, $\mathbf{\Theta}^{\mathbf{RO}}$, which preserves the topology of the observed RPE network while increasing the intensity of benchmarking incentives. The corresponding equilibrium quantities are given by

$$\mathbf{q}^{\mathrm{RO}} \;=\; (2\mathbf{I} + \Sigma + \mathbf{\Theta}^{\mathbf{RO}} \circ \Sigma)^{-1}(\mathbf{b} - \mathbf{c}). \tag{3.25}$$

Strict-dominant counterfactual. This counterfactual nests the previous exercise and strengthens the reallocation in the Relative-only case by giving strict RPE objectives priority whenever they are present. Specifically, for firms whose contracts include any strict RPE objective, we set the weights on all absolute goals and all index-based relative goals to zero and scale the strict RPE weight to 100% of performance-based pay. For firms that use relative performance evaluation but do not have strict RPE (i.e., they rely solely on index-based RPE), we set the weights on absolute goals to zero and rescale their index-based relative goals proportionally to sum to 100%. Firms that do not use RPE in the baseline remain unchanged.

This counterfactual produces an environment in which strict RPE becomes the exclusive benchmark whenever it exists, while firms lacking strict goals still rely entirely on relative performance. The resulting matrix of weights, $\mathbf{\Theta}^{\mathbf{SD}}$, preserves the structure of the observed RPE network but increases the strength of benchmarking incentives relative to the Relative-only counterfactual. The corresponding equilibrium allocation is

$$\mathbf{q}^{\mathrm{SD}} \;=\; (2\mathbf{I} + \Sigma + \mathbf{\Theta}^{\mathbf{SD}} \circ \Sigma)^{-1}(\mathbf{b} - \mathbf{c}). \tag{3.26}$$

4 Model Implementation and Validation

We now explain how we use the data to construct empirical counterparts of key objects of the model and how they are used to identify the model. Table 1 presents a comprehensive mapping of the variables in our model to their respective data sources.

4.1 Managerial Incentives and RPE Weight Matrices

This subsection maps the structure of executive compensation contracts into the set of matrices that summarize managerial incentives in the model. Following the economy-wide indexing convention introduced in Section 3.2, each empirical weighting matrix is defined over the full set of firms, managers, contracts, and goals, with zero entries for non-existent links[8]. We start from the goal level. The goals in executive contracts always specify one or more performance metrics used to determine vesting. For relative goals, the performance metric typically depends on the firm's rank or percentile within its designated peer group. Since such rank-based objectives are not analytically tractable, we approximate them by assuming that the reward depends on the probability that the focal firm's performance exceeds the *average* performance of its peers. This formulation captures the intuition behind percentile-based evaluation (often referencing the median, 25th percentile, or 75th percentile) while yielding a smooth and differentiable objective that facilitates aggregation and estimation.

We assume a performance metric $\mathcal{M}_{it}$[9] is an affine transformation of the realized firm's profit. This reduces the problem of comparing the firms' performance across several metrics to comparing their profits.

$$\mathcal{M}_{it} \;=\; \beta_{it}^{\mathcal{M}}(\pi_{it} - f_{it}) + o_{it}, \tag{4.1}$$

where π_{it} is the operating profit of the firm, o_{it} a linear shifter, and f_{it} represents an additional stochastic operational shock. Crucially, $\beta^{\mathcal{M}}$ is the sensitivity of metric $\mathcal{M}$ to profits π, $\frac{\partial \mathcal{M}_{it}}{\partial \pi_{it}} = \beta_{it}^{\mathcal{M}}$[10]. and is exogenous to the equilibrium strategy profile $\mathbf{q}$[11]. These sensitivities map the (endogenous) realized profits to the metric chosen by the firm i in year t, allowing us to embed the real contracts from the data into our model.

Note that we introduced an additional fixed-cost term, denoted f_i, which differs from the fixed component d_i introduced in Section 3.1. Whereas d_i represents overhead labor requirements that are deterministic and constant within the firm's production technology, f_i represents an idiosyncratic operational cost shock that makes realized firm performance stochastic. Introducing f_i allows firm outcomes to differ across managers even under identical market conditions, enabling us to define the probability that the focal firm's

[8]For example, if the economy has M managers and K contracts in a given year, and Manager 5 has only contracts 17 and 44, the economy-wide matrix $\mathbf{W}^u$still includes the entire fifth row, w_{5k} for all $k = 1, \ldots, K$. All non-existent links—i.e., all pairs $(5, k)$ with$k \neq 17, 44$—are recorded as zeros. This ensures that all weighting matrices share a common dimension.

[9]The metric is specific to a firm goal and year. To avoid notation we omit the goal g and firm i subscripts.

[10]This implies the existence of one sensitivity $\beta_{it}^{\mathcal{M}}$ for each firm and metric and year.

[11]If it were, the derivative $\frac{\partial \mathcal{M}_{git}}{\partial \pi_{it}}$ would be a more complex object. Since the model is static, the sensitivity $\beta_{it}^{\mathcal{M}}$ of each performance metric must be constructed from predetermined accounting variables and current profits. Thus, when a metric is forward-looking, such as stock price or TSR, we do not use its market-based realization to compute $\beta_{it}^{\mathcal{M}}$. Instead, we map these goals to the profit-linked component of the metric using lagged balance-sheet information. These relative goals remain fully included in the construction of $\mathbf{W}^r$ and the resulting $\mathbf{\Theta}$ network.

performance exceeds that of its peers. For tractability, we assume that $f_{it} \sim \mathrm{U}(0, F_{it})$, with F_{it} proportional to the firm's net property, plant, and equipment (PPENT in Compustat). This uniform specification yields closed-form outperforming probabilities. Economically, f_i encompasses unmodeled managerial inputs (such as effort or execution quality) and idiosyncratic luck that affect realized firm profits but are not explicitly chosen in the model.

To illustrate how the outperforming probabilities arise, consider Return on Assets (ROA) as the metric of interest. A firm's realized ROA is expressed as the ratio of its realized net profit to lagged fixed assets[12].

$$\mathrm{ROA}_{it} \equiv \frac{NetProfit_{it}}{FixedAssets_{it-1}} = \frac{\pi_{it} - f_{it}}{FixedAssets_{it-1}} \tag{4.2}$$

We denote $\beta_{it}^{ROA} = \frac{1}{FixedAssets_{it-1}}$ as the sensitivity of ROA to realized profits, where fixed assets are proxied by total assets (AT) from Compustat. Following this reasoning, we compute the sensitivities $\beta_{it}^{\mathcal{M}}$ for all firms and metrics they adopt employing balance sheet data in Compustat to approximate the original financial metrics as closely as possible.

When firm i is benchmarked against the ROA of its peer firms in a relative goal, the relevant reward depends on the probability that firm i outperforms the average peer performance[13]$\overline{\mathrm{ROA}}_t$, a proxy for the percentile, typically the median of peer performance,

$$\Pr\left(\mathrm{ROA}_{it} > \overline{\mathrm{ROA}}_t\right) = \Pr\left[(\pi_{it} - f_{it})\beta_{it}^{\mathrm{ROA}} > \frac{1}{|\mathcal{P}_g|}\sum_j (\pi_{jt} - f_{jt})\beta_{jt}^{\mathrm{ROA}}\right] \tag{4.3}$$

where $\mathcal{P}_g$ represents the set of peer firms specified in this relative goal and $|\mathcal{P}_g|$ the number of peers, as reported in the ISS IncentiveLab or the index constituents data. This representation makes explicit that managerial incentives depend on the difference between the firm's own profit and the average benchmarked profit of its peers, both adjusted for their asset sensitivities.

Under the uniform specification $f_{it} \sim \mathrm{U}(0, F_{it})$, we can express this probability in closed form . Specifically,

$$r_{it}^{\mathrm{ROA}} = \Pr\left(f_{it} \le \pi_{it} - \frac{1}{|\mathcal{P}_g|}\sum_{j\in\mathcal{P}_g}\frac{\beta_{jt}^{\mathrm{ROA}}}{\beta_{it}^{\mathrm{ROA}}}\left(\pi_{jt} - f_{jt}\right)\right) = \frac{1}{F_{it}}\left[\pi_{it} - \frac{1}{|\mathcal{P}_g|}\sum_{j\in\mathcal{P}_g}\frac{\beta_{jt}^{\mathrm{ROA}}}{\beta_{it}^{\mathrm{ROA}}}\pi_{jt}\right] + C_{it}, \tag{4.4}$$

where the constant C_{it} collects terms that depend only on the exogenous distribution of peer shocks. In empirical implementation, this affine expression is interpreted as an expected reward rather than a literal probability, since any truncation outside the $[0, 1]$ range is absorbed into C_{it}. This linearization shows that the reward from a relative goal can be written as a linear function of firm profits once we assume a uniform distribution of f_{it}. It follows that the contribution of each peer's performance to firm i's expected reward can be represented as a weight applied to that peer's profit:

$$r_{it}^{\mathrm{ROA}} = \sum_j w_{ij,t}^{\mathrm{ROA}}\pi_{jt} + \text{const}, \qquad \text{where} \qquad w_{ii,t}^{\mathrm{ROA}} = \frac{1}{F_{it}}, \qquad w_{ij,t}^{\mathrm{ROA}} = -\frac{1}{|P_g|}\frac{\beta_{jt}^{\mathrm{ROA}}}{\beta_{it}^{\mathrm{ROA}}}\frac{1}{F_{it}}, j \in \mathcal{P}_g, j \neq i. \tag{4.5}$$

Under a *Relative* goal, managers thus attach a negative weight to the profits of peer firms, while under an *Absolute* goal the reward depends only on the firm's own profit with weight $1/F_{it}$. Although the discussion has used ROA for concreteness, the same derivations apply to any performance metric $\mathcal{M}$, with sensitivities

[12]In this case $o_{it} = 0$

[13]\footnote{Although peer ROA is defined at the firm-peer level as ROA_{jt}, the benchmark summarizes these values and therefore does not carry the j subscript.}

$\beta_{it}^{\mathcal{M}}$ defined analogously. Note that for metrics whose realizations are market-based (e.g., stock price or TSR), the sensitivity $\beta_{it}^{\mathcal{M}}$ is computed from the profit-linked component of the metric using lagged accounting variables, consistent with the static nature of the model. In this way, we obtain the profit-based weights $w_{ij,t}^{r}$ that focal firm i assigns to peer firm j in a goal, which directly give rise to the goal-to-contract aggregation matrix $\mathbf{W}^r$.

In the data, each contract k in ISS Incentive Lab specifies several performance goals $g \in G$, each associated with a vesting weight reported as *percentVest*[14]. This vesting weight informs the relative importance of objectives but do not reflect that different goals may apply to different performance windows, which often only partially overlap. Because our model is static, we convert these multi-year structures into an annual allocation by first assigning each goal its *percentVest* share of the contractual fair value, as defined in Section 2, and then distributing this value across years in proportion to the fraction of the goal's performance period that falls in each year. A more detailed discussion is provided in the Appendix B.

The procedure yields goalValue_{kg}, which represents the monetary fair value assigned to objective g in contract k for that year. The corresponding weight w_{kg}^{e} is obtained by normalizing these values within each contract, dividing goalValue_{kg} by the sum of all objective-level fair values in contract k:

$$w_{kg}^{e} = \frac{\text{goalValue}_{kg}}{\sum_{g' \in G} \text{goalValue}_{kg}}, \qquad \sum_{g \in G} w_{kg}^{e} = 1 \tag{4.6}$$

This normalization makes w_{kg}^{e} directly comparable across contracts and ensures that each row of $\mathbf{W}^e$ represents the relative allocation of performance-based pay across goals within a given contract.

Each manager m may be linked to one or more contracts with her firm, as firms activate incentive plans every year. This is a feature we observe in the data where the median observation of the dataset has 4 active contracts in one year. [15]. Having constructed the goalValue_{kg}, we calculate the monetary value of a contract k in a given year as $\text{contractValue}_{\,k} = \sum_g \text{goalValue}_{kg}$, and use it to weight contracts when aggregating to the manager level. Let K_m denote the set of contracts associated with manager m. The entries of the resulting contract-to-manager matrix $\mathbf{W}^u$ is specified as

$$w_{mk}^{u} = \frac{\text{contractValue}_{\,k}}{\sum_{k' \in K_m} \text{contractValue}_{\,k'}}, \qquad \sum_{k \in K_m} w_{mk}^{u} = 1. \tag{4.7}$$

At the firm level, we assume there is a pricing manager at each firm i who makes the firm's strategic decisions, such as setting production (q) and pricing (p) decisions, by aggregating the incentives of all managers employed by the firm. Each manager's influence on the firm's objective is proportional to the total expected payout from their contracts within that firm. Let M_i denote the set of managers employed by firm i, K_m the set of contracts held by manager m, and K_i the set of contracts associated with firm i. We define the manager value in firm i as

$$\text{managerValue}_{im} = \sum_{k \in K_m} \text{contractValue}_k. \tag{4.8}$$

[14] The raw weights can be noisy due to incomplete reporting or totals that do not sum to one. We harmonize and normalize the goal weights within each contract to obtain a consistent allocation of performance sensitivity. When some goal shares are unreported, we allocate the residual mass evenly across the missing goals within the same contract before renormalization. For contracts that contain only absolute goals, within-contract weights are immaterial for the model (effectively implying no relative component).

[15] For contracts whose performance periods span multiple calendar years, we allocate the contract's value across years in proportion to the share of the performance period that falls in each year (e.g., based on the number of months in each calendar year). For simplicity, a contract covering three full years with a total expected value of $300,000 would contribute $100,000 to each year. The general rule and additional examples are described in Appendix B.1.1.

The manager-to-firm matrix $\mathbf{W}^v$ is then given by

$$w_{im}^v = \frac{\text{managerValue}_{im}}{\sum_{m' \in M_i} \text{managerValue}_{im'}}, \qquad \sum_{m \in M_i} w_{im}^v = 1. \tag{4.9}$$

Using the executive compensation data and firm balance sheet data, we thus construct the four weighting matrices, $\mathbf{W}^r, \mathbf{W}^e, \mathbf{W}^u$ and $\mathbf{W}^v$. We then combine them to obtain the composite matrix $\mathbf{W} = \mathbf{W}^v\mathbf{W}^u\mathbf{W}^e\mathbf{W}^r$, and normalize it by dividing each row by its diagonal entry so that each firm assigns a weight of one to itself. The resulting matrix $\mathbf{\Theta}$ that summarizes the RPE links across firms in the real world.

After constructing the baseline matrix $\mathbf{\Theta}$, we also generate two counterfactual versions that modify the allocation of goal weights while keeping all other steps—contract-, manager-, and firm-level aggregation—unchanged. Specifically, we reconstruct the goal-to-contract matrix $\mathbf{W}^e$ under alternative rules that reassign the within-contract shares w_{kg}^e across goals. For each contract k and goal g, let w_{kg}^e denote the baseline share and $\tilde{w}_{kg}^{e,s}$ the counterfactual weight in scenario $s \in \{\text{Relative-only}, \text{Strict-dominant}\}$.

In the *Relative-only* scenario, we consider all firms whose contracts include at least one relative-performance objective (strict or index-based). For these firms, we assign zero weight to all absolute (non-relative) goals in any contract that contains a relative objective, and we preserve the baseline proportions across all relative-performance goals and scale them proportionally to sum to 100% within each contract. In the *Strict-dominant* scenario, we give priority to strict RPE whenever it is present. For firms whose contracts include any strict RPE objective, we assign zero weight to both absolute goals and index-based relative goals in any contract that contains a strict RPE objective, and we scale the strict RPE weight to 100% of performance-based pay. For firms that use index-based RPE but do not have strict RPE, we set the weights on absolute goals to zero and scale their index-based relative goals to 100%. Firms that do not use RPE remain unchanged.

In both cases, the modified within-contract weights satisfy

$$w_{kg}^{e,s} = \frac{\tilde{w}_{kg}^{e,s}}{\sum_{g' \in G} \tilde{w}_{kg'}^{e,s}}, \qquad \sum_{g \in G} w_{kg}^{e,s} = 1. \tag{4.10}$$

where $s \in \{\text{Relative-only}, \text{Strict-dominant}\}$indexes the counterfactual rule and$\tilde{w}_{kg}^{e,s}$ denotes the post-adjustment (pre-normalization) weight. Each counterfactual goal matrix $\mathbf{W}^{e,s}$ is then combined with the unchanged higher-level matrices to form

$$\mathbf{W}^{(s)} = \mathbf{W}^v\mathbf{W}^u\mathbf{W}^{e,s}\mathbf{W}^r, \qquad \theta_{ij}^{(s)} = \frac{w_{ij}^{(s)}}{w_{ii}^{(s)}}. \tag{4.11}$$

In this way, the counterfactual networks $\mathbf{\Theta}^{(s)}$ differ from the empirical benchmark only in how performance-based pay is reallocated across goals, which enables us to isolate the effect of alternative RPE structures on firm-level incentives and equilibrium outcomes.

4.2 Other Model Inputs

Besides the incentive matrices introduced above, the model requires additional inputs that map observed firm characteristics into the technological primitives of the framework. To this end, we use Compustat financial statements to infer firms' cost structures and constructing performance metrics. We use product-similarity data to inform differentiation and competition in product markets.

Table 1: Variable Definitions and Mapping to Data

Panel A: Observed Variables

Notation	Description	Measurement	Source
$p_i q_i$	Revenues	Revenues	Compustat
$c_i q_i$	Total Variable Costs	Costs of Goods Sold	Compustat
d_i	Fixed Costs	Selling, General and Administrative Costs	Compustat
$\mathbf{a}_i'\mathbf{a}_j$	Cosine Similarity	Word frequencies in 10-K Business Description	Hoberg and Phillips (2016)
θ_{ij}	RPE weight	Function of β_i, Contract structure, Number of peers	ISS Incentive Lab

Panel B: Identified Variables and Parameters

Notation	Description	Identification
α	Weight on Common Characteristics	$= 0.12$ as in Pellegrino (2025)
q_i	Output	$\mathbf{q}$ such that $\pi + \mathbf{d} = \mathbf{diag}(\mathbf{q})(\mathbf{I} + \mathbf{\Theta} \circ \Sigma)\,\mathbf{q}$
c_i	Marginal Cost	$= \text{COGS}_i / q_i$
$(\mathbf{I} + \Sigma)$	$\partial \mathbf{p} / \partial \mathbf{q}$	$= (1 - \alpha)\mathbf{I} + \alpha \mathbf{A}'\mathbf{A}$
$\mathbf{b}$	Demand Intercept	$= \mathbf{c} + (2\mathbf{I} + \Sigma + \mathbf{\Theta} \circ \Sigma)\,\mathbf{q}$

Revenue and cost functions. Firm profits are computed as

$$\pi_i = p_i q_i - \mathrm{TVC}_i - d_i. \tag{4.12}$$

All the components can be constructed from Compustat accounting data. Revenues are measured by total sales (*SALE*). Variable costs are taken from costs of goods sold (*COGS*), and fixed costs from selling, general, and administrative expenses (*XSGA*). We exclude firms with negative revenues, COGS, or profit margins. To make welfare metrics comparable over time, all monetary values are deflated by the hourly labor compensation in non-farm business (COMPNFB series in FRED), indexed to the level of 2019.

Performance Metrics. Section 4.1 introduces the performance metric $\mathcal{M}$ and its sensitivity $\beta^{\mathcal{M}}$ which maps realized profits into the metric used in executive contracts. To implement these objects empirically, we construct the sensitivities $\beta_i^{\mathcal{M}}$ for each firm-metric pair using observable accounting data from Compustat. For metrics such as ROA and ROE, the sensitivities follow directly from their accounting definitions. For example, for ROE we use $\beta_i^{ROE} = \frac{1}{Shareholders'Equity_{i,t-1}}$, and we compute the remaining metric sensitivities in the same manner for all metrics reported in IncentiveLab. These empirical objects directly provide the $\beta^{\mathcal{M}}$ terms that enter equation 4.1.

Product similarity. To capture product market proximity, we use the text-based measure of Hoberg and Phillips (2016). Each firm's 10-K filing is converted into a 61,146-dimensional vector of word frequencies v_i, normalized by its Euclidean norm to obtain $\mathbf{a}_i = \mathbf{v}_i / \|\mathbf{v}_i\|$. Taking the dot product, we obtain the similarity matrix

$$\mathbf{A}'\mathbf{A} = [\, \mathbf{a}_i' \mathbf{a}_j \,]_{i,j}, \tag{4.13}$$

whose entries measure proximity of firms' product descriptions in the underlying vocabulary space. Firms with higher textual similarity are therefore interpreted as operating in more closely competing product markets.

4.3 Identification

All of the unobserved variables in the model are identified subject to parameters α, the degree of horizontal differentiation between goods. We will first show how to identify the remaining variables conditional on α and then illustrate our procedure for obtaining α.

Similar to Ederer and Pellegrino (2025), we express the vector of firm economic profits π and fixed costs $\mathbf{d}$ in terms of the quantity vector $\mathbf{q}$ and the matrices Σ and $\boldsymbol{\Theta}$, and find the $\mathbf{q}$ that satisfied the following equation:

$$\boldsymbol{\pi} + \mathbf{d} \;=\; \mathrm{diag}\,(\mathbf{q})\,(\mathbf{I} + \boldsymbol{\Theta} \circ \Sigma)\,\mathbf{q} \tag{4.14}$$

After obtaining q_i, we can derive the vector of prices and the cost function intercepts:

$$p_i \;=\; \frac{\mathrm{Revenues}_i}{q_i} \qquad \text{and} \qquad c_i \;=\; \frac{\mathrm{COGS}_i}{q_i} \tag{4.15}$$

Then, we derive the demand intercept b_i as

$$\mathbf{b} \;=\; \mathbf{c} + (2\mathbf{I} + \Sigma + \boldsymbol{\Theta} \circ \Sigma)\,\mathbf{q} \tag{4.16}$$

The mapping from Hoberg and Phillips (2016)'s cosine similarities to the GHL demand system requires two assumptions:

To link product market proximity in the data to substitution patterns in the model, we follow the mapping strategy of Pellegrino (2025) and Ederer and Pellegrino (2025), which interprets the cosine similarity of

Hoberg and Phillips (2016) as a measure of common product characteristics. This mapping rests on the standard assumption that the common product-characteristic space relevant for substitution is spanned by the HP vocabulary so that firms' word-frequency vectors proxy for product attributes, and that for each firm the observed text vector is proportional to its true characteristic vector up to a permutation, implying that cosine similarity in text space reflects relative proximity in product space.

Finally, we calibrate the substitution scaling parameter α using the same procedure adopted in Ederer and Pellegrino (2025). α governs the level of overall elasticity of substitution across products and can be inferred from an observed inverse cross-price elasticity and other firm-level observables such as revenues, costs, and HP cosine similarities. We calibrate α to match the benchmark value of 0.12 reported in Nevo (2001) as in Pellegrino (2025).

4.4 Validation

We conduct a set of validation exercises to assess the empirical plausibility of the Generalized Hedonic Linear (GHL) demand block. The procedure follows Pellegrino (2025) and Ederer and Pellegrino (2025) and characterizes a detailed three-step validation. First, the text-based similarity network of Hoberg and Phillips (2016) reproduces well-defined clusters that align with industry classifications, indicating that it captures meaningful product differentiation. Second, the similarity scores successfully predict firms' self-reported competitors in 10-K filings, confirming their reliability as measures of market rivalry. Finally, the demand elasticities implied by the GHL system are comparable in sign and magnitude to those estimated in benchmark IO studies such as Berry et al. (1993); Nevo (2001); Goeree (2008). For further details, see Pellegrino (2025).

5 Empirical Analysis

After we have provided a thorough discussion of the institutional details and the theory we now discuss the key findings from data and our model.

5.1 RPE Network in the Product Space

We begin by visualizing the network of RPE connections across all publicly listed firms in our sample, as shown in Figure 2. Each node represents a publicly listed firm, and an edge between two nodes indicates the existence of at least one contractual benchmarking relationship between their executives. The network exhibits a clear core-periphery pattern: a small set of large, diversified corporations sit at the center, connected to many others, while numerous smaller firms appear at the periphery with few links. These central firms are both frequent adopters of RPE and common choices as peers, reflecting their prominence in defining market benchmarks. Overall, RPE connections tend to link firms operating in related economic environments, where managerial performance is assessed relative to firms that are comparable in scale, exposure, or investor base rather than confined to narrow product-market rivalries.

Figure 3 compares the RPE network to the HP product similarity network, where link weights measure textual similarity in firms' product descriptions. Each observation represents a firm pair (i, j) that appears in both datasets. The horizontal axis measures product similarity $a_i \cdot a_j$, computed as the cosine similarity of the two firms' product descriptions. The vertical axis reports the RPE link. In our model, RPE links enter negatively because a manager's payoff decreases with better peer performance, and thus we plot $|\theta_{ij}|$, the absolute value to capture the strength of the benchmarking relationship. The height of each bar corresponds to the frequency of firm pairs falling into each bin.

Figure 2: Network of Peer Relationships

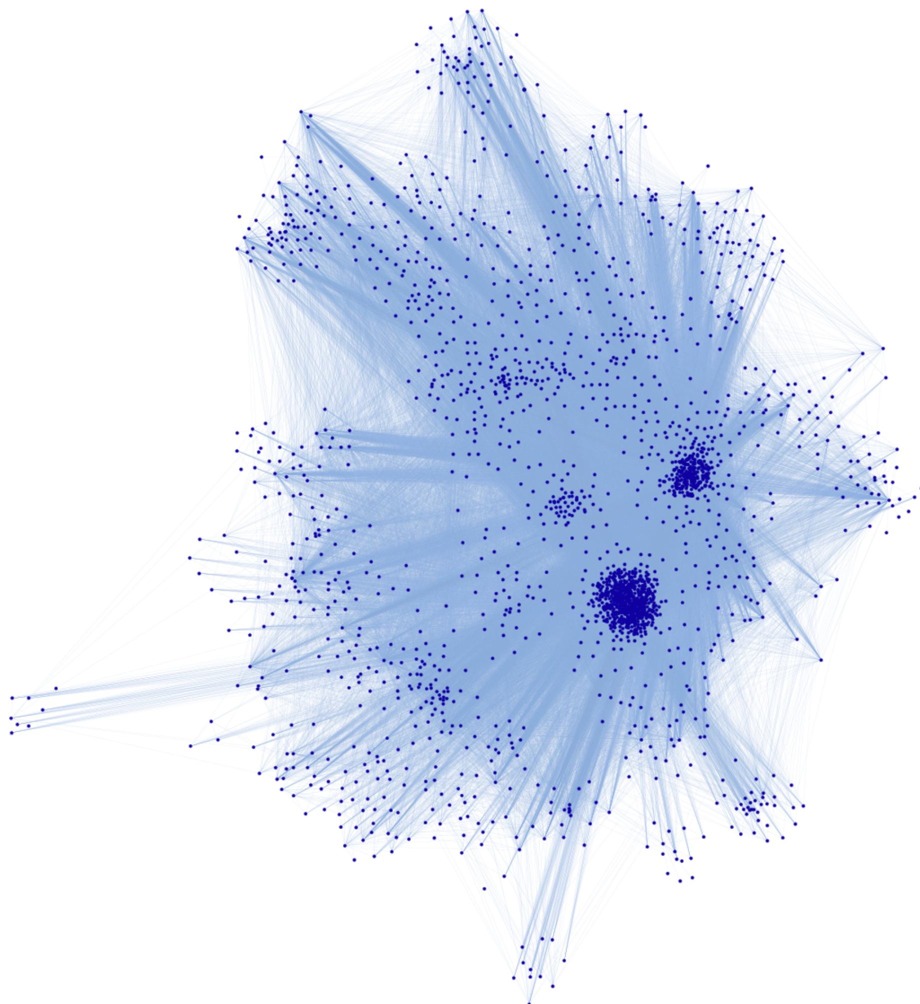


Figure Notes: The plot represents the full network of peer relationships in year 2016 that emerges from our theory of firm level incentives by applying the OpenOrd algorithm of Martin et al. (2011). There are 2241 nodes and more than 100,000 edges.

The figure shows that the two networks partially overlap. The distribution is highly concentrated near the origin, indicating that many firm pairs neither operate in closely related product markets nor are linked through explicit performance comparisons. A sizable portion of RPE connections also occurs between firms with limited technological or demand-side proximity. Nonetheless, a visible ridge appears along the diagonal where greater product similarity coincides with stronger RPE links. This pattern suggests that firms offering more similar products are more likely to be tied through relative-performance evaluations, consistent with the view that the competitive effects of RPE are concentrated among direct rivals. This evidence motivates the quantitative exercises that follow, which measure how the observed network of managerial benchmarking interacts with firms' strategic behavior in the product market.

Figure 3: Extensive and Intensive Margin Adoption of RPE

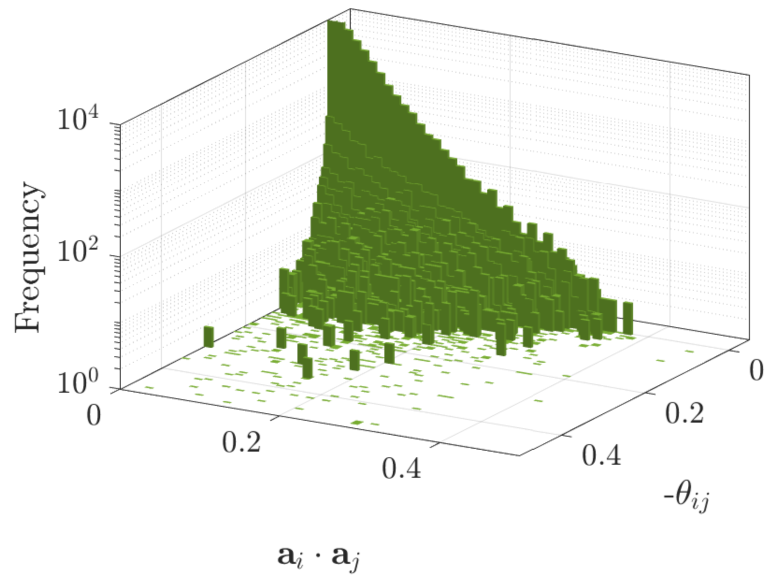


FIGURE NOTES: The 3D plot displays the joint distribution of product similarities computed by Hoberg and Phillips (2016) and the peer weights that emerge from our theory of firm level incentives.

5.2 Aggregate Product Market Effects of RPE

Having described the structure of the RPE network, we now quantify its aggregate implications for product market outcomes. Our analysis is static in nature but can be applied to annual firm-level data, allowing us to trace the evolution of RPE effects over time. Specifically, we compare the equilibrium allocation under the observed RPE weights with a benchmark Cournot economy in which managers are rewarded solely based on absolute firm performance, and we repeat this comparison for each year from 2006 to 2021. This approach captures both cross-sectional difference and time variation in firm strategies and welfare effects.

Figures 4-5 summarize the main findings. For each firm in each year, we compute the percentage difference in quantity and markup under the RPE equilibrium relative to its Cournot benchmark, and then take the revenue-weighted average across firms. Markup is defined as the price-to-cost ratio p_{it}/c_{it}. Figure 4 displays these aggregate changes, showing that in equilibrium with RPE, firms set slightly lower prices and expand quantities relative to the Cournot benchmark, reflecting the pro-competitive incentives induced by relative performance evaluation. The resulting changes in market outcomes are modest in aggregate: output rises by roughly 0.09%, and average markups decline by 0.06%. Welfare increases by less than 1%.

From an antitrust perspective, it it particularly informative to see how much of the welfare gains can be attributed to firm profits and consumer surplus. Decomposition shows that the gains accrue mainly to consumers. RPE raises consumer surplus by about 0.1% while lowering firm profits by a comparable magnitude[16]. Because corporate profits represent only about one-fifth of total surplus, this redistribution results in a small but positive welfare gain.

The time-series evidence indicates that these effects remain remarkably stable over time. As shown in Figure 5, total welfare in the RPE equilibrium fluctuates between 0.03% and 0.07% above the Cournot benchmark throughout 2006-2021, with no discernible upward trend. This stability contrasts with the sharp

[16]Note that quantities and markups are revenue-weighted, whereas the profit component of welfare is profit-weighted.

Figure 4: RPE Equilibrium vs. Standard Cournot: Firm Strategies

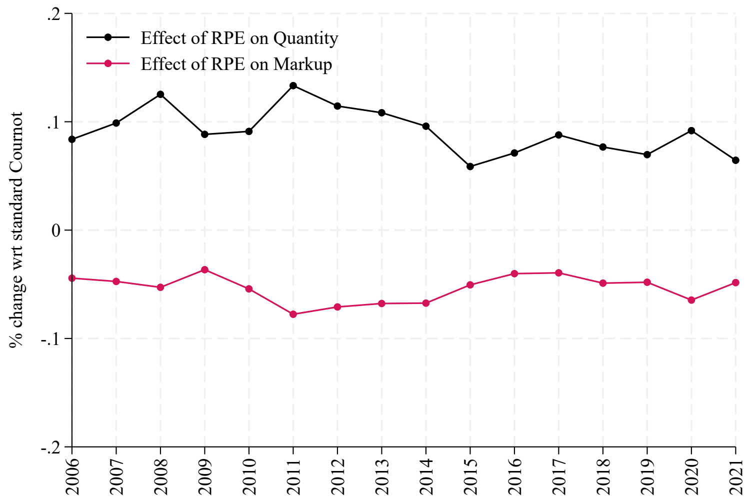


Figure Notes: The graph displays the percentage changes in firm strategies in RPE equilibrium relative to the standard Cournot from 2006 to 2021. The green and blue curves plot the evolution of the weighted-average changes in firm quantities and markups in RPE economy compared to Cournot.

Table 2: Heterogeneity across RPE Types

	Strict RPE	Index-based RPE
Average Number of Peers	12.41	484.42
Average Product Similarity	0.14	0.03

increase in the share of firms adopting RPE during the same period. Although RPE has become far more prevalent in executive compensation, its aggregate impact on competition and welfare has not strengthened accordingly.

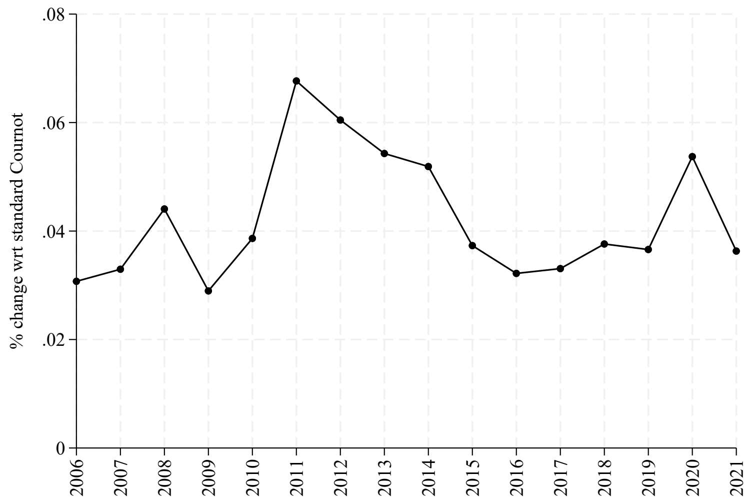
5.3 Heterogeneity in RPE Adoption and Firm Behavior

This disconnect between rising adoption and stable product market effects suggests that the aggregate impact of RPE depends not merely on whether firms adopt RPE, but on *how* they do so. As documented in Section 2, firms implement relative performance evaluation through two broad channels: some specify an explicit narrower set of peer groups, while others benchmark against broad market or sector indices. These contractual choices generate very different peer structures both in size and in product-market proximity, and therefore imply heterogeneous effects on firms' competitive behavior that can help explain why the observed aggregate effects remain small.

Table 2 compares the breadth and similarity of peer groups across the two RPE modes. Strict RPE contracts list on average 12.4 peers with an average product similarity score of 0.14, indicating relatively focused benchmarking among firms that operate in similar economic environments. By contrast, Index-based RPE exposes managers to index constituents numbering nearly 500 firms, with an average similarity score of

Figure 5: RPE Equilibrium vs. Standard Cournot: Welfare and Distributional Effects

(a) Panel (a): Change in Welfare



(b) Change in CS and Firm Profits

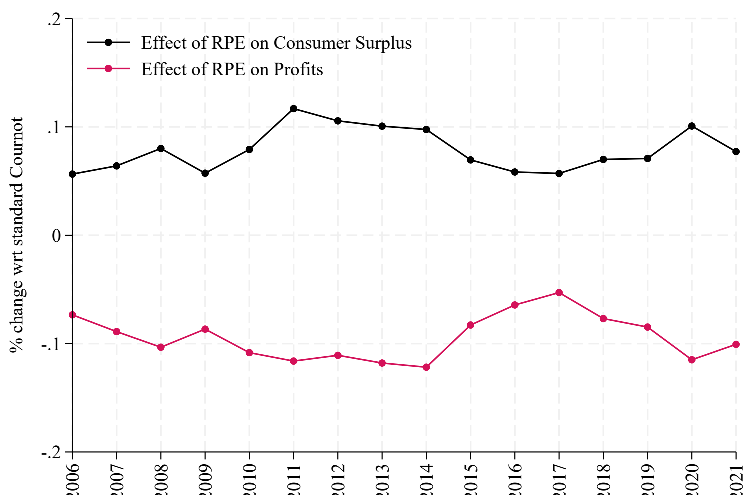


Figure Notes: Panel (a) of the figure plots the percentage changes in total welfare in RPE equilibrium relative to the standard Cournot from 2006 to 2021. Panel (b) plots the percentage changes in firm profits and consumer surplus in RPE equilibrium compared to the standard Cournot from 2006 to 2021.

Figure 6: RPE vs. Cournot Allocation: Quantity and Price Changes by Group, 2016

(a) Quantities (b) Prices

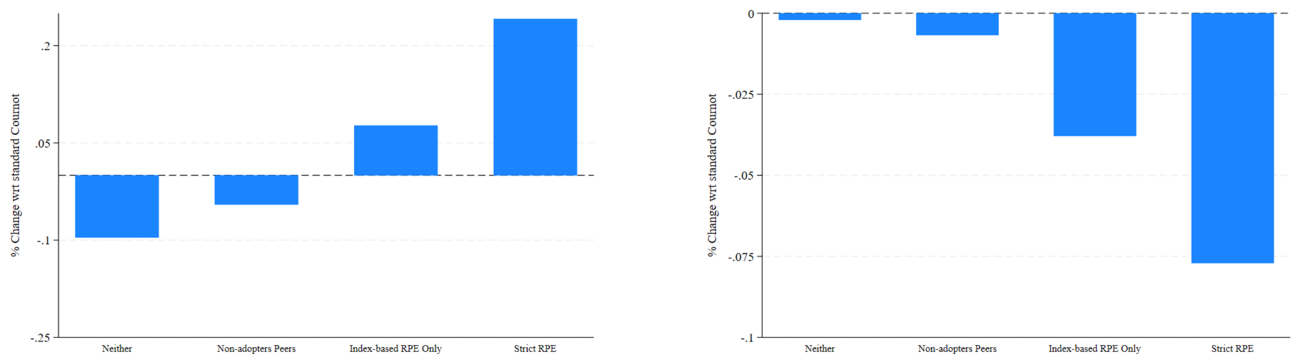


FIGURE NOTES: The graphs display the percentage change in quantities, Panel (a), and prices, Panel (b), under the RPE allocation aggregated by RPE group, relative to the standard Cournot allocation (no RPE).

0.03, reflecting benchmark groups that are far broader and substantially less connected in product space.

We then use this distinction to classify firms into four categories according to their role in the RPE network: (i) Strict RPE Adopters, which are firms who adopt at least one Strict RPE contract. (ii) Index-based RPE adopters, which adopt RPE in Index-based mode only. (iii) Non-adopter peers, which refer to firms that do not adopt RPE themselves but appear as peers in other firms' contracts. (iv) Neither, firms that are neither RPE adopters nor peers. This classification captures variation in firms' own incentive structures as well as the indirect exposure created when a firm becomes a target in other firms' benchmarking.

Figure 6 summarizes the responses across these four groups. Panel (a) reports the revenue-weighted average of the firm-level percentage change in quantities, computed as the weighted average of $q_i^{\text{RPE}}/q_i^{\text{Cournot}} - 1$, across firm i in the group, relative to their Cournot benchmarks. Output responses display a clear gradient across the RPE network. Strict RPE adopters increase quantities by about 0.25 percentage points, whereas Index-only adopters adjust much less, at roughly 0.06 percentage points. Firms that do not adopt RPE, whether or not they appear as peers, reduce output slightly, with declines ranging from 0.05 to 0.10 percentage points. This pattern illustrates that RPE's competitive impact is strongest where benchmarking is narrow and weakest where incentive links are diffuse or absent.

Panel (b) of Figure 6 presents the corresponding changes in equilibrium prices. All four groups price more aggressively under RPE, but the magnitude of the adjustment varies. Strict RPE adopters cut prices by close to 0.10 percentage points, reflecting the targeted incentives they face. Index-only adopters reduce prices by a more modest amount, around 0.03 percentage points. Firms outside the core of the RPE network show only minimal price reductions, generally within one basis point. Together with Panel (a), these results indicate that RPE strengthens competitive pressure, but its effects are most pronounced for firms connected through strict RPE.

To better understand the product market effects of RPE over time, we examine how the two types of RPE evolve from 2006 to 2021. Figure 7 plots the distribution of firms by the intensity of Strict RPE, measured as the share of compensation linked to goals with Strict RPE, for the year 2006 and 2021. While RPE adoption becomes far more common by 2021, most of the adopters do not benchmark heavily against explicit peer groups. Among RPE adopters in 2021, more than 40% use exclusively Index-based benchmarking, and another 25% assign less than 20% of compensation to Strict RPE. Only a small share place substantial weight on narrowly defined peer groups, in sharp contrast to the more balanced intensity distribution observed in

Figure 7: Extensive and Intensive Margin Adoption of RPE

(a) Firm-level compensation weight on Strict RPE goals, 2006 (b) Firm-level compensation weight on Strict RPE goals, 2021

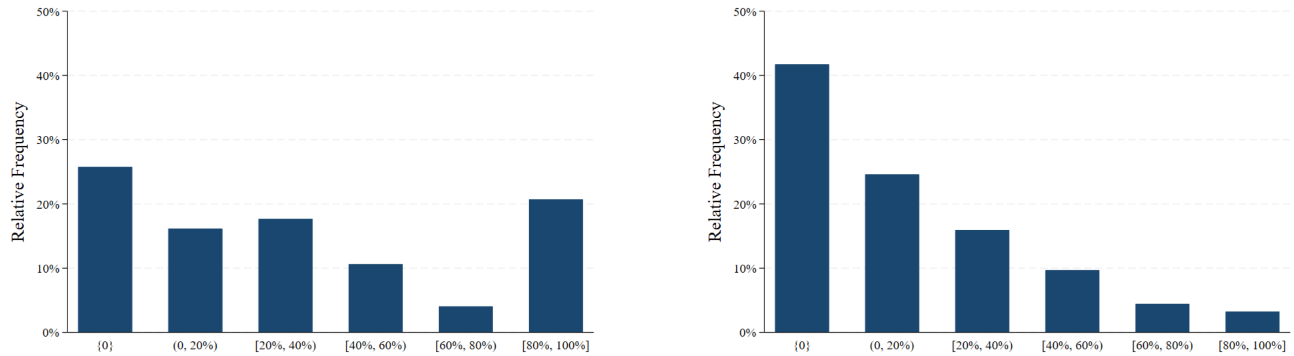


FIGURE NOTES: This graph presents the distribution of firms by Strict RPE intensity for the years 2006 and 2021. Strict RPE intensity is measured as the proportion of a firm's total compensation allocated to Strict RPE objectives. The bin {0} represents firms with no Strict RPE adoption, and the bin (0, 20%) includes firms where the compensation weight on Strict-RPE goals falls between 0 and 20%, and so on.

2006.

This evolution provides a natural explanation for why aggregate product market effects remain stable over time. The expansion of RPE adoption is driven almost entirely by firms adding Index-based benchmarks, which tie managerial incentives to large and heterogeneous sets of firms rather than to close rivals. Because Strict RPE does not become more prevalent, the marginal adopter introduces only weak competitive pressure, leaving equilibrium quantities, prices, and welfare effectively unchanged despite the broader diffusion of RPE.

5.4 Intensive Margin Counterfactuals

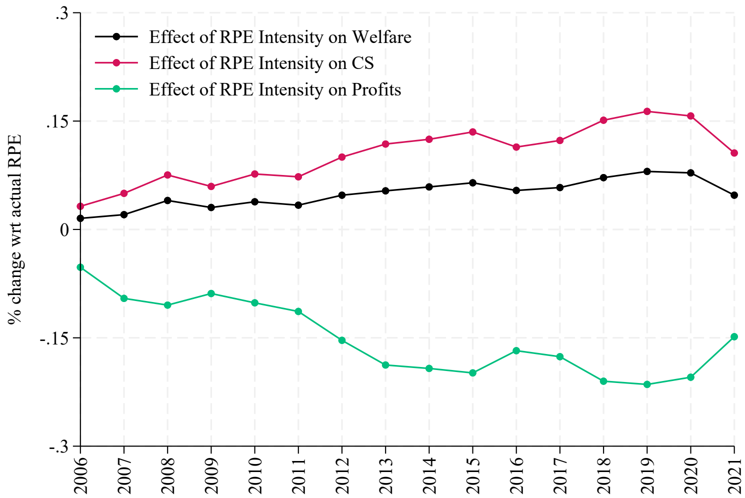
The evolution of adoption patterns suggests that the modest aggregate impact of RPE is not driven by weak underlying mechanisms, but rather by the way firms choose to implement RPE in practice. To assess how much stronger the competitive effects of RPE could be under more intensive use, we conduct counterfactual exercises that strengthen the intensity of relative incentives while keeping the set of RPE adopters fixed. Our main analysis focuses on the Strict-dominant RPE counterfactual in which all RPE-adopting firms operate in a setting where one hundred percent of executive compensation is tied to relative performance. This scenario isolates the intensive margin effect of RPE. The Relative-only counterfactual delivers similar qualitative patterns and is reported in the Appendix.

Figure 8 demonstrates the results of the Strict-dominant RPE counterfactual. Panel (a) plots percentage changes in welfare relative to the actual RPE equilibrium. Under Strict-dominant RPE, welfare is about 0.02 percentage points higher than in the observed RPE equilibrium in 2006, and the gain rises to roughly 0.05 percentage points by 2021. Measured against the Cournot benchmark, this corresponds to an increase in total welfare from around 0.05 percentage points in 2006 to approximately 0.1 percentage points in 2021.

Breaking down the components of welfare reveals that the gains are driven almost entirely by consumers. Consumer surplus increases from roughly 0.03 percentage points above the Cournot benchmark in 2006 to more than 0.1 percentage points in 2021. In contrast, firm profits fall more sharply than in the observed RPE equilibrium, declining from about -0.05 percentage points to roughly -0.2 percentage points. Since corporate profits represent a small share of total surplus, their decline is outweighed by the larger rise in consumer

Figure 8: Strict-dominant RPE Counterfactual vs. Actual RPE: Welfare Effects and Firm Strategies

(a) Change in Welfare



(b) Change in CS and Firm Profits

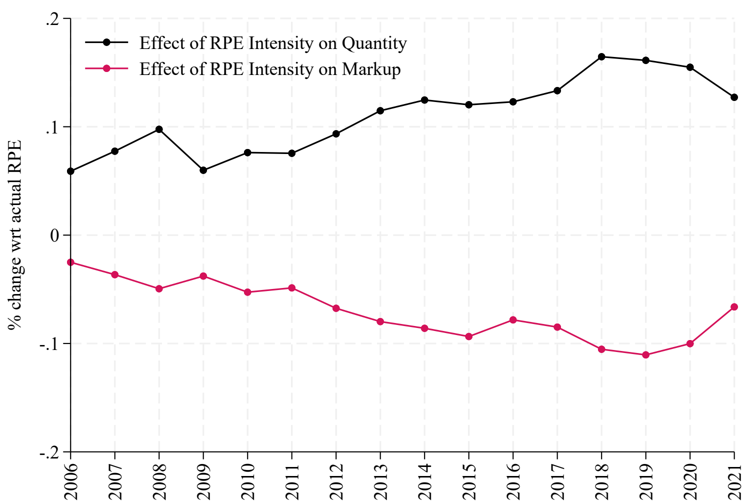


Figure Notes: The graph plots the percentage changes of welfare effects and firms strategies in **Strict-dominant RPE counterfactual** equilibrium compared to **actual RPE** equilibrium. Panel (a) plots the evolution of relative changes in total welfare (black curve), consumer surplus (blue curve), and corporate profits (green curve). Panel (b) plots the evolution of relative changes in quantities and markups.

Figure 9: Strict-dominant RPE Counterfactual vs. Actual RPE: Firm Profits By Group

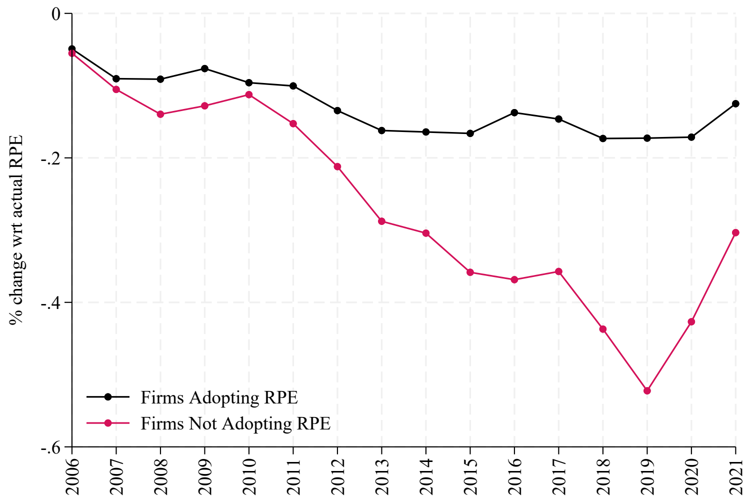


FIGURE NOTES: The graph plots the percentage changes of profits by group in **Strict-dominant RPE counterfactual** equilibrium compared to **actual RPE** equilibrium. The green and blue curves plot the evolution for RPE adopters and non-adopters, respectively.

surplus, yielding a net increase in overall welfare.

Panel (b) displays the corresponding changes in equilibrium quantities and prices, again relative to the actual RPE equilibrium. With all compensation tied to relative performance, firms expand quantities and reduce prices more aggressively than under observed RPE. Output rises by roughly 0.2 to 0.3 percentage points, and prices fall by a similar magnitude. These adjustments reflect the stronger incentives to outperform peers that arise when relative targets dominate executive compensation for adopting firms.

The Strict-dominant RPE counterfactual also introduces a clear upward trend in competitive pressure that is not present under actual RPE. To understand where this time pattern comes from, it is useful to examine how profits evolve separately for adopters and non-adopters. The four categories used in Section 5.3 collapse naturally into two groups in this setting, since the counterfactual strengthens incentives only for firms that adopt RPE.

Figure 9 reports the corresponding revenue-weighted changes in firm profits under the Strict-dominant counterfactual relative to the actual RPE equilibrium. Profits decline for both groups as incentives intensify, but the decline is substantially larger for non-adopters. Among adopters, the revenue-weighted profit difference between the Strict-dominant counterfactual and the actual RPE equilibrium widens from about -0.05 percentage points in 2006 to around -0.20 percentage points in 2021, while for non-adopters the corresponding gap grows from roughly -0.05 percentage points to nearly -0.50 percentage points over the same period. This widening gap explains the aggregate time trend under the Strict-dominant counterfactual: stronger relative incentives shift competitive advantages toward adopting firms, and these differences become more pronounced over time. Additional results for quantities and markups in the Appendix confirm this pattern.

Taken together, these findings show that the small and time-invariant product market effects observed in the data are driven by the limited intensity with which firms employ RPE in practice. When relative performance plays a larger role in executive pay, competitive pressure strengthens substantially and increases over time, revealing the considerable unrealized potential of RPE.

6 Conclusions

This paper studies the effects of relative performance evaluation on product market competition through its effects on executive incentives. Using a novel dataset on compensation contracts, we document a sharp rise in RPE adoption on the extensive margin but find that the within-firm share of executive compensation linked to relative performance remains low. Furthermore, most firms benchmark against broad equity indices rather than a custom peer group, reducing its potential competitive impact.

A general equilibrium oligopoly model suggests that RPE can drive more aggressive competition, reducing markups and increasing output. Yet, our empirical findings indicate that these effects remain moderate due to the low intensity of Strict RPE adoption. Counterfactual simulations suggest that greater reliance on Strict RPE could amplify competitive benefits and enhance consumer welfare through lower prices.

Our findings contribute to research on executive compensation, market structure, and corporate governance. The contrast between theoretical predictions and observed adoption patterns highlights the need to understand how firms structure incentives beyond standard principal-agent models. The growing prevalence of Index-based RPE suggests firms may prioritize risk-sharing over competitive incentives, which is a good question for further study on RPE.

Overall, this study underscores the importance of executive compensation design in shaping competitive dynamics. While RPE adoption has grown, its impact on firm behavior remains nuanced and dependent on how benchmarking relationships are structured. A deeper understanding of these mechanisms is crucial for evaluating the implications of RPE on market efficiency, firm strategy, and economic welfare.

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Online Appendices

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A Appendix

A.1 Mapping of Metrics to Balance Sheet

In the tables below we report the formulae used to construct the sensitivities of the metrics adopted by firms to profits. When forced to use a different metric, we opt for the closest balance sheet concept available as a proxy. Define:

- π: operating profits
- P: stock price
- D: debt
- E: equity
- A: total assets
- R: revenue
- T: tax expenses
- Inv: investment
- I: interest expenses
- S: total sales

B Data

B.1 ISS Incentive Lab

The data was obtained though WRDS. The coverage of ISS in the U.S. is defined as the union of the set of the largest 750 companies (as defined by market cap) and the set of all companies within the S&P 500. If a company enters the coverage universe, the analysts of ISS backfill the data to 1998 (or the companies' first trading date if this is after 1998)[17].

The datasets we use are:

1. *Grants of Plan Based Awards* (GPBA), contains information at the contract level such as the contract identifier, the total dollar value associated with the achievement of the objectives agreed upon in the contract. The dataset does not undergo any preliminary data cleaning procedure.

[17] The source of this information is a direct email exchange with an analyst of ISS.

Table 3: Taxonomy of Relative Performance Metrics 1/2

Metric	correct	Formula	Imputed Sensitivity $\beta^{\mathcal{M}}$	Data Coverage
Stock Price	Growth	$\frac{\pi_t}{\pi_{t-1}}$	$\frac{1}{\pi_{t-1}}$	44.13%
TSR	-	$\frac{P_t - P_{t-1} + d_t}{P_{t-1}}$	$\frac{1}{\pi_{t-1}}$	21.16%
Others	-	Highly differentiated and uncommon metrics.	-	9%
ROIC	Level	$\frac{\pi_t - Div_t}{D_t + E_{t-1}}$	$\frac{1}{D_{t-1} + E_{t-1}}$	4.26%
ROIC	Growth	$\frac{ROIC_t}{ROIC_{t-1}}$	$\frac{1}{(D_{t-1} + E_{t-1}) \cdot ROIC_{t-1}}$	-
ROE	-	$\frac{\pi_t}{0.5(E_t + E_{t-1})}$	$\frac{1}{E_{t-1}}$	3.3%
Earnings per Share	Level	$\frac{NI_t - Pref.Div._t + / - ExtraItems_t}{WAvgCS_t}$	$\frac{1}{CSHO_{t-1}}$	3.29%
Earnings per Share	Growth	$\frac{EPS_t}{EPS_{t-1}}$	$\frac{1}{EPS_{t-1} \cdot E_{t-1}}$	-
Sales	Growth	TBD	TBD	3.12%
Operating Income	Level	$GP_t - OE_t - Dep_t - Amort_t$	1	1.92%
Operating Income	Growth	$\frac{OpInc_t}{OpInc_{t-1}}$	$\frac{1}{\pi_{t-1}}$	-
Operating Income	Per Share	$\frac{OpInc_t}{0.5(Equity_t + Equity_{t-1})}$	$\frac{1}{E_{t-1}}$	-
ROA	-	$\frac{\pi_t}{A_{t-1}}$	$\frac{1}{A_{t-1}}$	1.6%
Profit Margin	-	$\frac{OperatingProfits_t}{R_t}$	$\frac{1}{R_{t-1}}$	1.36%
Cashflow	-	TBD	TBD	0.78%
FFO	-	I suspect these are all REITs		0.72%
Earnings	Levels	π_t	1	0.69%
Earnings	Growth	$\frac{\pi_t}{\pi_{t-1}}$	$\frac{1}{\pi_{t-1}}$	-
Gross Revenues	-	TBD	TBD	0.69%
Non-Financial	Drop	Drop	Drop	0.61%

Table 4: Taxonomy of Relative Performance Metrics 2/2

Metric in the data	correct	Formula	Imputed/Assumed Sensitivity	Data Coverage
ROI	Levels	$\frac{\pi_t}{Inv_{t-1}}$	$\frac{1}{Inv_{t-1}}$	0.59%
EBITDA	Growth	$\frac{EBITDA_t}{EBITDA_{t-1}}$	$\frac{1}{\pi_{t-1}}$	0.49%
EBITDA	Margin	$\frac{EBITDA_t}{Revenues_{t-1}}$	$\frac{1}{Revenues_{t-1}}$	-
EBITDA	Per Share	$\frac{EBITDA_t}{CSOutstanding_{t-1}}$	$\frac{1}{CSHO_{t-1}}$	-
EBT	Levels	$\pi_t + T_t$	1	0.32%
EBT	Margin	$\frac{EBT_t}{R_{t-1}}$	$\frac{1}{R_{t-1}}$	-
EBT	Margin, Growth	$\frac{EBT_t}{R_{t-1}} \frac{1}{EBTMargin_{t-1}}$	$\frac{1}{R_{t-1} \cdot EBTMargin_{t-1}}$	-
EVA	Growth	$\frac{NOPAT_t - (InvestedCapital_t \cdot WACC_t)}{NOPAT_{t-1} - (InvestedCapital_{t-1} \cdot WACC_{t-1})}$	TBD	0.25%
EBIT	Levels	$\pi_t + I_t + T_t$	1	<0.2%
EBIT	Growth	$\pi_t + I_t + T_t$	$\frac{1}{\pi_{t-1}}$	-
Net Income	Levels	π_t	1	<0.2%
Net Income	Growth	$\frac{\pi_t}{\pi_{t-1}}$	$\frac{1}{\pi_{t-1}}$	-
Debt Related	-	TBD	TBD	<0.2%
Operational	-	not feasible	not feasible	<0.2%
ROC	-	$\frac{\pi_t}{D_{t-1}+E_{t-1}}$	$\frac{1}{(Debt_{t-1}+Equity_{t-1})}$	<0.2%
Operating Profits	-	$NetSales_t - COGS_t$	TBD	<0.2%
Same Stores Sales	-			<0.2%
ROS	-	$\frac{EBIT_t}{S_{t-1}}$	$\frac{1}{S_{t-1}}$	<0.2%

2. *Relative Objectives*, provides information at the contract-goal level, specifically about *relative objectives* and the weight that each of these goals was assigned in the data. The preliminary cleaning of this dataset involves harmonization of the index names given the low quality of the variables *relativeBenchmark* and *relativeBenchmarkOther* which contain information on the type of RPE the goal belomngs to and the index name used as a benchmark in case the goal belongs to index based RPE. After the harmonization procedure, we drop all the relative goals who belong to index based RPE and for which we do cannot construct a peer group (because of lack of index constituents data).

3. *Absolute Objectives*, provides information at the contract-goal level, specifically about *absolute objectives* and the weight that each of these goals was assigned in the data. The dataset does not undergo any preliminary data cleaning procedure.

4. *Relative Peers*, for each contract, provides the names of the firms that are part of peer groups, when such peer groups are explicitly reported in the proxy materials. The first step we take on the raw data is to first drop the observations where there is no peer information at all, namely the ones where both the variables *peerCIK* and *peerTicker* are missing. We then drop all observations that are duplicates in terms of all the variables in the dataset.

The person to whom we referred the most is Harriet Barr who is no longer working at ISS Incentive Lab (harriet.barr@iss-stoxx.com).

B.1.1 Goal Weights in the Data

Section 2 constructs contract fair value using achievement probabilities across performance thresholds. Since contracts span multiple years and objectives while our model is static, we must assign annual values to each objective to construct the weights w^e_{kg}. IncentiveLab provides the variable percentVest, which weights each goal within a contract (summing to 1) but offers no temporal breakdown. We assume managers value each time period uniformly for a given objective.

We construct w^e_{kg} in three steps. First, multiply each contract's fair value (from Section 2) by its percentVest to allocate value across goals. Second, distribute each goal's value across years proportionally to the months of its performance period falling in each year. Finally, normalize: w^e_{kg} equals this annual goal value divided by the total value across all goals in that year. The following nested examples illustrate this procedure.

Single-Year Contract. Consider a contract with fair value 100 containing objective R1 with performance period from January 1 to December 31, 2010. Since $percentVest(R1) = 1$ and the period is confined to 2010, $w^e_{k,R1} = 1$ in 2010. The contract does not appear in other years.

Two Objectives, Same Period. Add objective A1 with $percentVest(A1) = 0.4$ and $percentVest(R1) = 0.6$. If both objectives span January 1 to December 31, 2010, their 2010 weights equal their percentVest values: $w^e_{k,A1} = 0.4$ and $w^e_{k,R1} = 0.6$.

Overlapping Periods. In the data it is also the case that goals bundled in the same contract have differing and overlapping performance periods. Let A1 span January 1, 2010 to June 30, 2011, while R1 remains in 2010 only. Fair value and percentVest values are unchanged. The implications for the contractual structure are that, in 2010:

- The annual goal value of A1 is $FairValue \cdot percentVest(A1) \cdot timeShare(A1, 2010) = 100 \cdot 0.4 \cdot 2/3 = 26.6$ because 2010 counts for 66.7% of the performance period of this goal.

- The annual goal value of R1 is $FairValue \cdot percentVest(R1) \cdot timeShare(R1, 2010) = 100 \cdot 0.6 \cdot 1 = 60$ because 2010 counts of 100% of the performance period of this goal.

where $timeShare(A1, 2010)$ represents how much of the performance period of goal A1 falls in the year 2010. Because of our assumption on the uniform valuation of time units $2/3$ of the monetary value of objective A1 gets allocated to 2010 and the rest to 2011.

The value of the contract in 2010 is the sum of the two fair values, 86.6. The implied weights w^e_{kg} are the fair values of the objectives normalized by their sum, $w^e_{k,A1} = \frac{26.6}{26.6+60} = 0.3072$ and $w^e_{k,R1} = \frac{60}{26.6+60} = 0.6928$.

In 2011:

- The annual goal value of A1 is $FairValue \cdot percentVest(A1) \cdot timeShare(A1, 2011) = 100 \cdot 0.4 \cdot 1/3 = 13.3$ because 2011 counts for only 33.3% of the performance period of this goal.

- The annual goal value of R1 is $FairValue \cdot percentVest(R1) \cdot timeShare(R1, 2011) == 100 \cdot 0.6 \cdot 0 = 0$ because 2011 counts of 0 of the performance period of this goal.

The total value of contract in 2011 is 13.3. And the weights are, $w^e_{k,A1} = \frac{13.3}{13.3} = 1$ and $w^e_{k,R1} = 0$.

This approach unbundles and rebundles objectives to correctly account for both relative importance and temporal heterogeneity within contracts.

B.2 RPE over Time and across Sectors

In this subsection we present a few general stylized facts about RPE in the US for the period we consider.

Fact 1, RPE is a local but fast growing phenomenon among large U.S. public companies. The adoption of RPE among large U.S. firms has steadily increased over the observed period 2006-2021, as depicted in Figure 1. In 2006, approximately 20% of large firms utilized RPE in their compensation structures. This share rose consistently over time, surpassing 30% by 2010 and reaching 50% by 2017, where it remained stable through 2019.

Fact 2, The share of total compensation at the sector level tied to RPE is heterogenous. Figure 10 depicts the RPE share of performance-based executive compensation of the mean firm across various sectors for 2006 and 2021. The data reveals a consistent pattern of decline in RPE usage across all sectors over this fifteen-year period. In 2006, Communication Services exhibited the highest RPE share (approximately 0.8), followed by Financials and Energy (both around 0.6). By 2021, while the sectoral ranking remained relatively stable, all sectors experienced substantial reductions in RPE utilization, with values generally falling to the 0.3-0.4 range. Notably, Energy retained the highest RPE share in 2021, while Health Care showed the lowest adoption rate in both periods, indicating persistent cross-sectoral differences in compensation design despite the overall downward trend.

Fact 3, Reciprocity is a key feature of RPE. As an example we consider the year 2016 to show this, yet the fact is common to all years in the sample.

- Virtually all firms (44) adopting both Index-based and Strict RPE are also target of a RPE contract (i.e. they are selected as peers). 79% are target to both Index and Strict RPE contracts, 9% of the firms are target to Index-based RPE contracts only, and 9% are target to Strict RPE contracts only.

- All firms (275) adopting RPE in Strict mode only are also target of a RPE contract. 85% are target to both Index-based and Strict RPE contracts, 15% are target to Strict RPE contracts only.

- All firms (184) adopting RPE in Index-based mode only are also target of an RPE contract. 87% are target to both Index-based and Strict RPE contracts, 13% of these are peers to Index-based RPE contracts only.

Figure 10: Relative share of performance based compensation 2006 vs 2021, by Sector

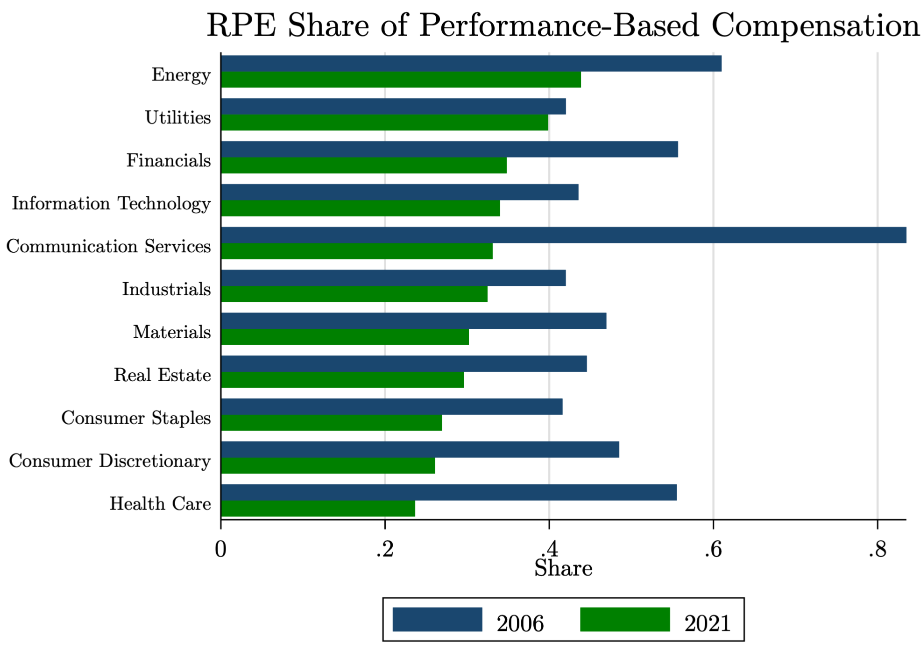

FIGURE NOTES: The figure reports the share of performance based compensation that is allocated to relative objectives as opposed to absolute objectives in each sector for the years 2006 and 2021. The sectors follow the GICS classification at the sector level.

C Index Constituent Data Sources and Construction

For 2006-2010, we scraped index constituent data from Global Financial Data (GFD) Finaeon, covering:

- S&P 500
- S&P 400
- S&P 1500
- S&P 600
- Nasdaq 100
- Dow Jones
- Russell 2000
- Russell 3000

We constructed industry sub-indices at four GICS aggregation levels (Sector, Industry Group, Industry, Sub-Industry) using the scraped data combined with Compustat.

For 2011-2021, Standard & Poor's Dow Jones Indices team provided proprietary historical constituent data for:

- S&P 500
- S&P 400
- S&P 600
- S&P Total Market Index

This information allows us to identify peer firms for Index-based RPE contracts where ISS Incentive Lab reports only the index name.

D Figures

Figure 11: Strict-dominant RPE Counterfactual vs. Actual RPE: Firm Strategies by Group

(a) Change in Quantity by Group

(b) Change in Markup by Group

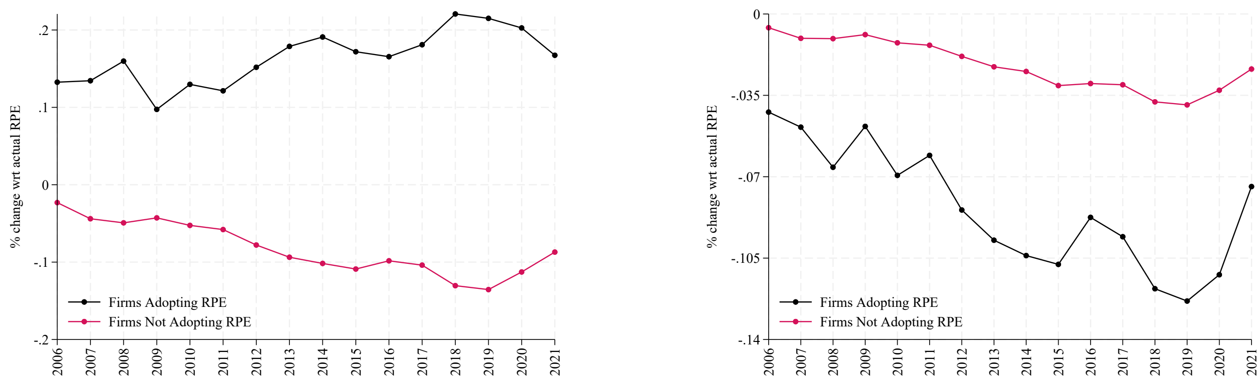

Figure Notes: The graph displays the percentage changes in quantities and markups by group in **Strict-dominant RPE** counterfactual relative to the **actual RPE** from 2006 to 2021. Panel (a) and (b) plot the changes in quantity and price, respectively. The green and blue curve plot the changes for firms adopting RPE and not adopting RPE, respectively.