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 contracts that benchmarks a manager's performance against that of a group of competitors. Economic theory predicts that firms who adopt RPE will display more aggressive product market conduct (i.e. charge lower prices). The extent of RPE adoption and its product market effects remain disputed: firm filings suggest that RPE is common, yet mangers' pay does not correlate with competitors' performance. We study the product market effects of RPE, using a general equilibrium oligopoly model with ultra-realistic managerial incentives, which we discipline with granular data from over 60,000 executive compensation contracts. We find that RPE adoption is widespread and increasing. However, pay remains largely tied to absolute rather than relative objectives, and relative performance is often measured against the broader stock market rather than a few close rivals. These adoption patterns significantly dampen the product market effects of RPE, thus reconciling the seemingly contradictory evidence. Counterfactual simulations suggest that RPE could enhance competition and consumer welfare by lowering markups and increasing output, but these effects remain muted under current adoption patterns.

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

Keywords: Competition, Executive Compensation, General Equilibrium, Market Power, Networks, Oligopoly, Relative Performance Evaluation, Text Analysis

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1 Introduction

Relative Performance Evaluation (RPE) is a well-known feature of executive compensation contracts: it consists of making executives' pay dependent on a firm's *relative performance* against a peer group, rather than on the firm's *absolute performance*: its primary goal, 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.

However, when considered in the context of oligopolistic competition between firms, RPE is predicted to have a lesser-known side effect – that is, to alter the product market conduct of adopter firms. When managers are rewarded for outperforming their competitors, their incentives shift from maximizing their own firm's profits to undercutting the profits of their peers [Aggarwal and Samwick, 1999]. Theory thus predicts that the adoption of RPE will result into more aggressive pricing and more intense product market competition. This behavior can reduce industry profits while benefiting consumers through lower prices and increased allocative efficiency. These pro-competitive effects have remained relatively understudied until recently, due to the limited availability of data on executive contracts [Gong et al., 2011, De Angelis and Grinstein, 2011].

The true extent of RPE adoption as well as its product market effects remain disputed. As summarized by Edmans, Gabaix, and Jenter [2017] in their review of the literarture, 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 appears instead to correlated with broader industry performance [Albuquerque, 2009, Jayaraman et al., 2021]. At the same time, recent econometric evidence based on newly-available executive compensation data shows at least some evidence of product market effects [see Bloomfield et al., 2022, Bloomfield, 2023, Bloomfield et al., 2023, Feichter et al., 2022]. In sum, the product market effects of RPE are still far from fully understood.

The aim of this paper is to provide the most comprehensive quantitative study yet of the product market implications of RPE adoption. In particular, we study its effects on firm profitability, consumer surplus, product prices and supply, by combining rich data on executive compensation contracts with a large-scale oligopoly model.

On the data side, we carefully process unstructured data on 60,000 executive compensation contracts from ISS IncentiveLab to extract detailed information on the structure of performance-based incentives, including the presence of relative v/s absolute incentives, contract durations, performance metrics, and peer information. This granularity enables us to translate complex, multi-objective contracts into measures of managers' pay sensitivity to competitors profits. The resulting dataset takes the form a weighted network, where firms are nodes and the edges reflect RPE relationships – specifically the negative weight that a firm puts on the profits of each competitor. Through the lens our model, this network, as well as its degree of overlap with the network of product market rivalries is the key determinant of the pro-competitive effects of RPE.

To quantify the product market effects of RPE, we develop a general equilibrium model of oligopoly with two key building blocks. The first is the Generalized Hedonic Linear (GHL) demand system based on Pellegrino [2025], which allows us to model product market competition among public firms at scale, and to measure product subsitution in a data-driven way using the product similarity data

Figure 1: RPE Active Contracts 2006-2021

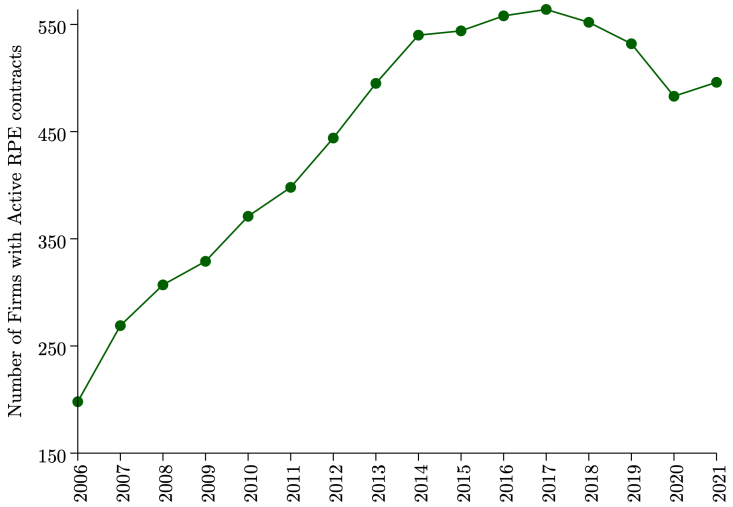


FIGURE NOTES: The lineplot describes the evolution of the number of U.S. publicly listed companies featuring active RPE contracts in a given year. The time period ranges from 2006 and 2021. The source of the data is the ISS Incentive Lab.

of Hoberg and Phillips [2016]. The second, and novel, component is a highly general and complex specification of each firm's objective function that results from the (linear) aggregation of the goals specified in its managers' pay contracts. The are four layers of aggregation: we go from individual performance goals to contract-level objective functions; we then aggregate contract-level objective functions to manager-level objective functions; finally, by aggregating across-different managers within the same firm, we obtain the firm's objective function. Because this structure mimics closely that of the IncentiveLab data we process: this allows us to use the RPE network derived from IncentiveLab data to structurally parametrize each firm's objective function, which depends not only both absolute and relative performance objectives - affect firms' competitive behavior.

Thanks to the tractability of the GHL framework, we can solve analytically the Nash-Cournot equilibrium of this generalized oligopoly model. We can then conduct counterfactual analysis to unpack the effects of of RPE on firm prices, supply and profitability, as well as its effect on consumer surplus.

Our analysis yields several key findings. First, we examine the degree of product market overlap between RPE peers. We find a positive correlation between product similarity, as measured by Hoberg and Phillips [2016], and the weights a focal firm assigns to peers in an RPE contract, indicating that RPE incentives may encourage firms to undercut rivals in product market competition. However, a substantial number of firms do not explicitly benchmark their performance against that of close competitors.

This pattern is likely driven by our second key finding: the heterogeneity in peer group selection for RPE adoption. While the use of RPE has become widespread, many firms benchmark against broad market indices, such as the S&P 500 or Russell 2000, rather than against a selected group 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 RPE, and their adoption is associated with more aggressive quantity and pricing strategies, consistent with the findings of Bizjak et al. [2022] and Feichter et al. [2022].

Third, our granular dataset allows us to analyze not only the extensive margin of RPE adoption—the share of firms incorporating RPE into contracts—but also the intensive margin, which captures the weight placed on RPE, particularly Strict RPE, compared to absolute performance evaluation. We document that among firms with active RPE contracts in 2021, around 40% rely exclusively on Index-based RPE, and another 25% allocate less than 20% of their contract value to Strict RPE. The relatively low weight placed on Strict RPE at the intensive margin potentially explains RPE's limited impact on product market competition.

Finally, we analyze the welfare implications of RPE adoption, comparing them to a world without RPE. Under observed adoption patterns, total welfare improves modestly ($\sim$0.05% annually), driven by consumer surplus gains (+0.1%) that offset corporate profit declines (-0.1%). Counterfactual scenarios in which firms place greater emphasis on relative performance objectives show welfare gains approximately twice as large (+0.1%), underscoring the limited real-world impact of current RPE intensity. Welfare improvements primarily arise from increased output and lower markups, particularly among Strict RPE adopters. However, larger firms dominate RPE adoption, and their aggressive strategies disproportionately affect smaller, non-RPE firms, which experience steeper profit declines.

Two papers are close to ours in spirit: Feichter et al. [2022] and Bloomfield [2023], which empirically study the relationship between competitive aggressiveness and peer group overlap for firms who adopt RPE. They find strong support for the "sabotage hypothesis" (as opposed to "collusion"). Sabotage refers to situations in which the firm engages in conduct harmful for the peers' performance, such as price undercutting, advertising campaigns, or product imitation. The sabotage hypothesis suggests that incentive plans based on relative performance can increase competitive aggressiveness among firms; for example when managers are evaluated against peers, they may engage in sabotage to improve their own relative performance. It also predicts that the level of competitive aggressiveness is increasing in reciprocity (i.e. when the focal firm is a peer to its own peers).

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. Our paper builds on this framework by introducing managerial incentives shaped by executive compensation contracts, allowing us to analyze how strategic interactions evolve under RPE.

Second, we contribute to the literature on executive pay, which documents its dramatic growth (Gabaix and Landier [2008], Edmans et al. [2017]) and influence on firm behavior (Kim and Lu [2011], Cziraki and Groen-Xu [2020]). Shi [2023] studies the effect of noncompete clauses using executive compensation data, and Chemla et al. [2024] develop a dynamic general equilibrium model of executive compensation with moral hazard, showing that firms' compensation choices create externalities by influencing executives' outside option. Complementing this literature, our findings

highlight the importance of considering the interaction between managerial incentives and market structure and analyzing the effects of executive compensation on 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 about RPE-induced "sabotage" (Feichter et al. [2022], Bloomfield [2023]) with empirical evidence of muted aggregate effects (Jayaraman et al. [2021]), demonstrating that outcomes depend critically on the alignment between benchmarking networks and product market rivalries.

Third, our work is closely related to the literature on market power in macroeconomics (De Loecker et al. [2020], De Loecker and Eeckhout [2018], Syverson [2019], Autor et al. [2020], Döpper et al. [2022]). We contribute to this literature by exploring how executive compensation, particularly RPE, influences competitive behavior and market power. A closely related paper is Bao et al. [2023], which also explores interactions between market structure and managerial incentives, but we take RPE adoption as the driver of competitive dynamics rather than treating market power as an exogenous primitive. Our findings suggest that RPE can mitigate market power by encouraging more aggressive competition, particularly when firms benchmark against specific peers.

We also relate to the work on performance pay and relative performance evaluation in personnel economics (Lazear and Rosen [1981], Lazear [2000]). Usually RPE is adopted within firms to perform evaluation and incentivize effort provision. However, for top executives, it is hard to establish a peer group within the firm, which is why firms resort contracts comparing the firm's performance to other firms performance. We study how this specific use of RPE transmits incentives across firms, by inducing a network over the set of publicly listed companies, thereby impacting product market competition.

Finally, our paper connects 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 examines how networks of input-output relationships propagate idiosyncratic shocks. While prior work focuses on production networks, we instead model two distinct networks: one capturing product market rivalries and another reflecting RPE benchmarking relationships. Methodologically, we connect to 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 both strategic complementarities (through product market interactions) and substitutabilities (through RPE incentives).

In summary, this paper bridges the gap between theory and empirics by providing a comprehensive analysis of the product market implications of RPE adoption. We show that while RPE has the potential to enhance competition and improve welfare, its effects are contingent on the nature of adoption and the alignment between benchmarking relationships and product market rivalries. As RPE adoption continues to grow, understanding these dynamics will be crucial for both firms and policymakers seeking to promote competitive markets and maximize consumer welfare.

The remainder of the paper is structured as follows. Section 2 provides a detailed overview of the data sources and methodology used in our analysis. Section 3 presents the theoretical framework, including the GHL demand system and the model of managerial incentives. Section 4 discusses the empirical results, including the time trends of RPE adoption and the product market effects of RPE. Section 5 concludes with a discussion of the implications of our findings for both theory and

policy.

2 Data

This section provides an overview of the data sources used in our analysis and the key variables relevant to model identification. A detailed discussion on how we incorporate these data into the model will be presented in Section 3.5.

2.1 Executive Compensation Data

To estimate the model, we must obtain fine-grained information about executive compensation contracts and their structure. To this end, we leverage data from the Institutional Shareholder Services (ISS), which we access through the Wharton Research Data Services (WRDS) platform. The information disclosed in the data became public following the obligation by the SEC to disclose all executive compensation information for the three highest paid executives in the proxy material. We restrict our attention to the period between 2006 and 2021. In this time span, there are around 650,000 absolute objectives and 77,000 Relative objectives, respectively, accounting roughly for 90% and 10% of the total number of objectives.

In the original dataset, 1196 unique firms adopt incentive plans that involve at least one objective based on RPE. The number of unique companies that adopt at least one objective based on RPE becomes 678 if we restrict the attention to incentive plans that do not involve absolute objectives.

2.1.1 The Jargon of Executive Compensation Contracts

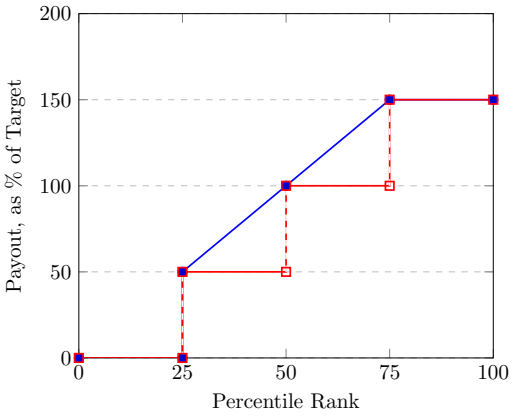
Each agreement between a firm i and executive m constitutes a *grant*, potentially resulting in an *award*. Grants comprise various *objectives* that determine whether the award vests fully, partially, or not at all. These objectives fall into two categories: performance-based (*Absolute* or *Relative*) and time-based. Performance-based objectives evaluate achievement against specific metrics, while time-based objectives simply require the passage of time. Our analysis focuses on performance-based contracts, which specify a metric and a payout function increasing in performance. These are the contracts that dominate the ISS Incentive Lab dataset.

For Absolute objectives, achievement is measured against predetermined numerical thresholds explicitly specified in the contract. In contrast, Relative objectives evaluate firm performance in comparison to a designated *peer group* of companies. This distinction is significant because with relative objectives, the executive's compensation depends not only on their own firm's performance but also on how it ranks against peer firms. Figure 2 illustrates the payout function for relative objectives. The following section examines these mechanisms in greater detail.

2.1.2 The Structure of Executive Compensation Contracts

Proxy materials report three thresholds and the associated payments to determine the payout to make under a contract as shown in Figure 2. The payment the executive receives is defined as a step (or piecewise linear) function of performance with kinks at the thresholds. These thresholds are labeled as (we report *verbatim*) "Threshold", "Target," or "Max", here listed in order of increasing

Figure 2: Payout Function Example



2020 PERFORMANCE GOAL	HOW MEASURED	WEIGHTING	THRESHOLD EARN 25%	TARGET EARN 100%	MAXIMUM EARN 175%
Relative TSR*	Cumulative GE TSR vs. S&P 500 Industrial Index	100%	35th percentile	55th percentile	80th percentile

FIGURE NOTES: The figure on top describes the payout function of relative objectives in the two most common forms. The x-axis reports. The red function describes the payout as a step function of the ranking whereas the blue function describes it as a piecewise linear function of the ranking. The bottom figure displays a concrete example of a relative objective extracted from the proxy materials of General Electric.

difficulty. All payments are specified relatively to the "Target" payment. Consequently, four are the possible outcomes in this context:

- The firm does not hit the Threshold level of the performance metric and *no payment* is awarded to the executive.
- The Threshold value is hit and a *fraction* of the Target payment is awarded to the executive.
- The Target value is hit and the *exact amount* of the Target payment is awarded to the executive.
- If the Max is hit and a *multiplier* of the Target payment is awarded to the executive.

This information at the contract level is in turn in important especially to understand the *notional contract value*. This variable together with two other variables explained here below are fundamental to understand how absolute and relative objectives are combined into a contract and how they affect managerial incentives.

- *performanceGrouping* encodes how objectives g comprised in a contract k, are combined. In the data, this variable appears as a series of symbols and brackets to form an interpretable language that, together with *percentVest* (see below), allows us to attribute the weights to each goal within a grant.
  A simple example from the data: the $performanceGrouping$ of a grant is given to be "{A1+R1}" which tells us that the grant involves two goals, one absolute and one relative. The plus sign tells us that the sum of the two goals accounts for 100% of the award. The two goals have attached a weight determining their relative importance. These weights are discussed in the next point.

- *percentVest* assigns a weight to each objective g, as part of a contract k. This weight is the percentage of the total award that depends on each objective. Following our running example, we could have *percentVest*(A1)=0.6 and *percentVest*(R1)=0.4.
- *Notional contract value,* y_k, is the expected amount of money the executive can receive for meeting *all the objectives* in contract k. For contracts whose compensation consists in the attribution of stocks (or options), the ISS dataset provides a fair value (in dollars) of these securities computed at the date when the contract is signed. However, no fair value is provided for all other contracts, whose payments are non-equity-based. Thus, we need to construct a fair value for these contracts starting from the four possible payments the manager faces when working towards an objective (namely, no payment, Threshold payment, Target payment, Max payment). To do so, we combine the information on these payments from the ISS Incentive Lab and data elaborated in a memorandum[1] produced by Compensation Advisory Partners, which gives a probability mass function taking the four possible payouts as the support for the goals. This function is however the same for all types of goals within the contracts. This allows us to approximate the fair value of a Non-Equity-based award by computing the *unconditional expected notional value* as follows:

  $$FairValue_k = \sum_{t=1}^{4} p(t)B(t)$$

  where t is defined as the occurrence where the performance falls between threshold t and threshold $t+1$, $p(t)$ is the probability of such event, and $B(t)$ is the payment accrued to the executive if the firm hits a certain threshold t but not the one above.

2.1.3 RPE Modes and Equity Index Data

As mentioned in the previous section, an important part of relative objectives are the *peer groups*. As already described in [Bloomfield et al., 2022], we observe two major modes of RPE in the data which differ in the type of peer groups they specify. On the one hand, *Strict RPE* entails a firm explicitly listing the names of the firms that have been selected to be part of the RPE peer-group. On the other hand, *Index-based RPE* involves selecting a pre-specified set of peers, usually an equity index like the S&P 500 or a subset of it like the S&P 500 Consumer Staples. The availability of the peer group information in the ISS data depends on the modes of RPE adopted in a given contract. ISS Incentive Lab explicitly reports the peer group's information only for Strict RPE objectives. For the index-based objectives, however, only the name of the index is reported, and no information on the underlying constituents is provided. To solve this problem, we undertake a significant scraping effort on the data we can access provided by Global Financial Data (GFD) Finaeon. This results in datasets covering the index constituents of S&P 500, S&P 400, S&P 1500, S&P 600, Nasdaq 100, Dow Jones, Russell 2000, and Russell 3000 every year from 2006 to 2010. Using the information from the scraped index data and Compustat, we construct sub-indices at the four levels of aggregation established by the Global Industry Classification Standard (GICS) namely, "Sector", "Industry Group", "Industry", "Sub-Industry", which also appear as benchmark groups. For the years 2011 to 2021, we have obtained proprietary information on historical index

[1]The content of the memorandum was discussed in a series of posts (Post 1 and Post 2)authored on the Harvard Law School Forum on Corporate Governance. The authors of the post are Michael Bonner and Melissa Burek, respectively principal and founding partner at Compensation Advisory Partners.

constituents by the Standard & Poor's Dow Jones Indices team for the following indices: S&P 500, S&P 400, S&P 600, S&P Total Market Index.

2.2 Financial and Product Similarity Data

Firm-level financial data is obtained from Compustat. On one hand, we extract information on firm revenues, costs of goods sold (COGS), and selling, general, and administrative (SG&A) expenses to map to estimate economic cost structures. On the other hand, we leverage the financial variables to construct proxies to the financial metrics specified in contracts. To make the welfare metrics comparable over time, we deflate every dollar amount by the hourly labor compensation in non-farm business (COMPNFB in FRED), indexed at the level of 2019.

Another key data component for estimating our model is the matrix of product similarity, $\mathbf{A}'\mathbf{A}$. Its empirical counterpart is first constructed by Hoberg and Phillips [2016, henceforth HP]. analyze 10-K filings to extract the language firms use to describe their products. This process results in a vocabulary of 61,146 words, each representing a distinct product characteristic[2].

3 Model, Identification, and Validation

To study the interaction between RPE and product market competition, we extend the model in Pellegrino [2025] introducing peer relationships from executive compensation contracts into the network game of Cournot oligopoly.

3.1 Generalized Hedonic-Linear (GHL) Demand System

The economy is populated by a representative household that determines how much to consume and work while owning all firms. Goods are supplied by I firms, indexed by $i \in \{1, 2, ..., I\}$, each producing a differentiated product. The GHL demand system builds on the hedonic demand approach [Lancaster, 1966, Rosen, 1974] which models each products a a bundle of characteristics. Each product possesses:

- N common characteristics indexed by $n \in \{1, 2, ..., N\}$.
- one idiosyncratic characteristic that is unique to each product and therefore has the same index i as the corresponding product.

A product i is compactly described by the N-dimensional column vector $\mathbf{a}_i$ in the common characteristics space

$$\mathbf{a}_i = \begin{bmatrix} a_{1i} & a_{2i} & \dots & a_{Ni} \end{bmatrix}', \tag{3.1}$$

[2] Hoberg and Phillips [2016] describe their methodology in the following way: "In our main specification, we limit attention to nouns (defined by Webster.com) and proper nouns that appear in no more than 25 percent of all product descriptions in order to avoid common words. We define proper nouns as words that appear with the first letter capitalized at least 90 percent of the time in our sample of 10-Ks. We also omit common words that are used by more than 25 percent of all firms, and we omit geographical words including country and state names, as well as the names of the top 50 cities in the United States and in the world."

which is of unit length[3], with each scalar a_{ni} denoting the number of units of common characteristic n of product i.

Combining all the product-specific vectors $\mathbf{a}_i$, we obtain an $N \times I$ matrix $\mathbf{A}$:

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

Let q_i be the units of the good produced by firm i. Then, the quantities of products can be expressed by the I-dimensional vector $\mathbf{q} = \begin{bmatrix} q_1 & q_2 & \cdots & q_I \end{bmatrix}'$. The total units of common characteristic n consumed in the economy are given by

$$x_n = \sum_{i=1}^{I} a_{ni} q_i \tag{3.3}$$

which yields $\mathbf{x} = \mathbf{A}\mathbf{q}$ in matrix form. We define y_i as the number of units of idiosyncratic characteristic of product i, and assume that each unit of good i provides exactly one unit of its corresponding idiosyncratic characteristic $\mathbf{y} = \mathbf{q}$.

The representative agent's utility function is quadratic in both common characteristics ($\mathbf{x}$) and idiosyncratic characteristics ($\mathbf{y}$). Moreover, the preferences feature linear disutility in the total number of hours of work supplied (H):

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

where b_n^x and b_i^q are characteristic-specific preference shifters associated respectively with common and idiosyncratic characteristics. $\alpha \in [0,1]$ governs the importance of common characteristics and hence the degree of *horizontal differentiation* among products. When $\alpha = 0$, the consumer only cares about idiosyncratic characteristics of the products making all producers monopolists. If $\alpha = 1$, only the common characteristics matter.

We close the model by making leisure the outside good. We assume that labor is the numéraire of this economy. The representative consumer optimally chooses a consumption bundle $\mathbf{q}$ taking the vector of prices $\mathbf{p}$ as given. Because the representative agent owns all the firms, she receives the aggregate profits Π on top of the labor income H earned by working. The household choice $\mathbf{q}$ abides by the following budget costraint

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

[3]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 normalization assumption on volumetric units (kilograms, pounds, gallons, etc.). The normalization consists in picking, for each good i, the volume unit 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.

Therefore, the consumer chooses a demand function $\mathbf{q}(\mathbf{p})$ to maximize the following consumer surplus function

$$CS(\mathbf{q}) \quad \stackrel{\text{def}}{=} \quad \mathbf{q}'(\mathbf{b}-\mathbf{p}) - \frac{1}{2}\mathbf{q}'\left[\mathbf{I}+\alpha\left(\mathbf{A}'\mathbf{A}-\mathbf{I}\right)\right]\mathbf{q} \tag{3.6}$$

where

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

and

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

Crucially, the entries, $\mathbf{a}_i'\mathbf{a}_j$ of the matrix $\mathbf{A}'\mathbf{A}$ in equation (3.6) are the *cosine similarities* between all firm pairs. Due to our normalization, the *cosine similarity* is bounded between 0 and 1. This implies that $0 \leq \sigma_{ij} = (\Sigma)_{ij} \leq \alpha, \forall i,j$. Intuitively when $\sigma_{ij} = \alpha$, product i and product j are maximally substitutable. In the opposite case they a perfectly differentiated and completely orthogonal in the space of common characteristics. Note that the overall substitutability between two goods, can be broken in two components: the first is *intrisic* and accounted for by the product characteristics; the second, being a preference parameter, is *subjective* to the household and accounted for by the parameter α. Hence the expression "maximally substitutable" when $\sigma_{ij} = \alpha$.

Finally, solving the household program yields the following demand and inverse demand functions

$$\text{Aggregate demand}: \quad \mathbf{q} \;=\; (\mathbf{I}+\mathbf{\Sigma})^{-1}(\mathbf{b}-\mathbf{p}) \tag{3.9}$$

$$\text{Inverse demand}: \quad \mathbf{p} \;=\; \mathbf{b} - (\mathbf{I}+\mathbf{\Sigma})\,\mathbf{q} \tag{3.10}$$

3.2 Production

Define h_i as the labor input acquired by firm i. Then labor market clearing requires:

$$H \;=\; \sum_i h_i \tag{3.11}$$

Since labor is the numéraire, h_i is also the total cost incurred by firm i. Assume that firm i's cost function takes a a quadratic form

$$h_i(q_i) \;=\; d_i \;+\; c_i^0 q_i \;+\; \frac{\delta_i}{2}\,q_i^2 \tag{3.12}$$

where d_i is the fixed cost, and $c_i \stackrel{\text{def}}{=} c_i^0 + \delta_i q_i$ is the marginal cost.

As it appears from equation 3.10, every firm's output q_i affects the price of all other products (p_j) in this economy. This is due to the fact that the inverse demand elasticiy $\partial p_i/\partial q_j$ is proportional to $\mathbf{a}_i'\mathbf{a}_j$, the product similarity between i and j. The closer these two firms are in the common characteristics space, the larger is this derivative in absolute value. Because of the symmetry of $\mathbf{A}'\mathbf{A}$, we have $\partial q_i/\partial p_j = \partial q_j/\partial p_i$.

The economic profit of firm i is therefore given by

$$\begin{aligned}\pi_i(\mathbf{q}) &\overset{\text{def}}{=} p_i(\mathbf{q}) \cdot q_i - h_i \\ &= q_i b_i - q_i^2 - \sum_{j \neq i} \sigma_{ij} q_i q_j - h_i\end{aligned}$$

3.3 Relative Performance Evaluation and Managerial Incentives

This section provides a mathematical exposition of the aggregation of managerial incetives in this economy. The I firms in the economy have in total M *managers* indexed by $m \in \{1, 2, ..., M\}$. With the word manager we refer to individuals with operational powers in the company such as the C-Suite and VPs. With some abuse of notation, we also refer to I (M) as the set of *firms* (*managers*) [4]. For each firm-manager pair, the manager's compensation package is specified in a *contract*, indexed by $k \in \{1, 2, ..., K\}$, where K is the total number of exective contracts in the economy as well as the set of contracts. Typically, a contract is structured as a bundle of *goals* on the focal firm's[5] performance, either its own performance (*absolute goals*) or the performance relative to a peer group of firms (*relative goals*). Let G denote the set of goals and also the aggregate number of goals in the contracts, and $g \in \{1, 2, ..., G\}$ the index of each goal. Our objective is to distill this rich structure of contracts into a matrix that describes the peer relationships between firms.

3.3.1 Goals

In each period, a firm incurs a stochastic fixed cost f_i , which follows a uniform distribution $f_i \sim U(0, F_i)$[6]. Therefore, the realized profit of the firm can be written as $(\pi_i - f_i)$, where π_i is the economic profit defined in Section 3.2. In an executive contract, a goal g of firm i usually specifies a *comparison metric* $\mathcal{M}_{gi}$ (e.g., TSR, ROIC) and an exogenous target T_{gi} on the metric. Assume a metric $\mathcal{M}_{gi}$ is linear in the realized profit

$$\mathcal{M}_{gi} = \beta_{gi}^{\mathcal{M}}(\pi_i - f_i) + o_i \tag{3.13}$$

where β_{gi} is the sensitivity of metric $\mathcal{M}_{gi}$ to a change in the realized profit of the focal firm i, and o_i is a constant.

The expected value that a manager obtains from the goal is proportional to the probability of hitting the target of the goal. For an absolute goal (a goal involving no peers), the metric target

[4] 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.

[5] In the context of RPE focal refers to the firm who is stipulating the contract. The term is opposed to peer which defines a

[6] The assumption of uniform distribution allows us to express the expected value of a contract κ_k as a linear function of economic profits π_i

T_{gi} is exogenous, thus the expected value γ_g follows

$$\gamma_g \;\propto\; Pr\left(\mathcal{M}_{gi} \geq T_{gi}\right) \;=\; Pr\left(\beta_{gi}\left(\pi_i - f_i\right) \geq T_{gi}\right) \;=\; Pr\left(f_i \leq \pi_i - \frac{T_{gi}}{\beta_{gi}}\right) \;=\; \frac{1}{F_i}\pi_i + C_{gi}$$

where the constant C_{gi} depends on T_{gi}, β_{gi}, and F_i, but is independent of the economic profit π_i and does not affect the incentives of managers. Without loss of generality, we normalize the constant term to 0.

The standard target of a relative goal specifies the targeted ranking (usually 50th percentile) among a group of competing firms $\mathcal{P}_g$ against which the focal firm is benchmarked (the number of firms in the peer group is represented by $|\mathcal{P}_g|$). We assume that the focal firm i takes the aggregate effects of peer firms' stochastic fixed costs as given, which means $\frac{1}{|\mathcal{P}_g|}\sum_j \beta_{gj} f_j$ is exogenous to firm i and does not affect firm i's decisions[7]. Taking sample average as a proxy for the sample median, we can write the goal value as

$$\begin{aligned}\gamma_g \;&=\; Pr\left(\beta_{gi}\left(\pi_i - f_i\right) \geq \frac{1}{|\mathcal{P}_g|}\sum_j \beta_{gj}\left(\pi_j - f_j\right)\right) \;=\; Pr\left(f_i \leq \pi_i - \frac{\frac{1}{|\mathcal{P}_g|}\sum_j \beta_{gj}\left(\pi_j - f_j\right)}{\beta_{gi}}\right) \\ &=\; \frac{1}{F_i}\left(\pi_i - \frac{1}{|\mathcal{P}_g|}\sum_j \frac{\beta_{gj}}{\beta_{gi}}\pi_j\right) + C_{gi} \qquad (3.14)\end{aligned}$$

Again, we normalize the constant term C_{gi} to 0. Therefore, the normalized value of absolute and relative goals become

$$\gamma_g \;=\; \frac{1}{F_i}\pi_i \qquad \text{and} \qquad \gamma_g \;=\; \frac{1}{F_i}\left(\pi_i - \frac{1}{|\mathcal{P}_g|}\sum_j \frac{\beta_{gj}}{\beta_{gi}}\pi_j\right), \qquad (3.15)$$

Define a $G \times I$ matrix $\mathbf{R}$ containing all goals, both absolute and relative. The (g, j)-entry takes value:

- $-\frac{\beta_{gj}}{|\mathcal{P}_g|\beta_{gi}}\frac{1}{F_i}$ if the focal firm i is benchmarked against firm j,
- 0 if the focal firm is not benchmarked against firm j,
- $\frac{1}{F_i}$ if $j = i$

Hence, an absolute goal (left formula in equation 3.15) implies that the firm is specifying a contract that puts zero weight on all other firms and positive own weight. On the other hand, a relative goal (right formula in equation 3.15) will put positive own weight and negative weights on the peers.

Below we present an illustrative example to clarify the structure of the matrix. Assume there are three firms $i = 1, 2, 3$, and three managers $j = 1, 2, 3$. The contracts are specified as below:

[7]Here we assume the competing firms affect the focal firm's decision through their profits (π_j) rather than individual shocks on fixed costs (f_j). In particular, this always holds when the number of peer firms is large, because by the law of large numbers, $\frac{1}{|\mathcal{P}_g|}\sum_j \beta_{gj} f_j \to \mathbb{E}\left(\beta_{gj} f_j\right)$, where $\mathbb{E}\left(\beta_{gj} f_j\right)$ is an constant.

1. Contract $k = 1$ is between firm 1 and manager 1, and contains two goals: $g = 1$ is an absolute goal, and $g = 2$ is a relative goal that is benchmarked against firm 2 and firm 3.
2. Contract $k = 2$ is between firm 1 and manager 3, and contains two goals: $g = 3$ is an absolute goal, and $g = 4$ is a relative goal that is benchmarked against firm 3 only.
3. Contract $k = 3$ is between firm 2 and manager 2, and contains three goals: $g = 5$ is a relative goal that is benchmarked against firm 1 and firm 3, $g = 6$ is a relative goal that is benchmarked against firm 1 only, and $g = 7$ is an absolute goal.
4. Contract $k = 4$ is between firm 3 and manager 3, and contains one goal: $g = 8$ is a relative goal that is benchmarked against firm 1 and firm 2.

In this example, there are $I = 3$ firms, $J = 3$ managers, $K = 4$ contracts, and $G = 8$ goals. So, $\mathbf{R}$ is an 8×3 matrix:

$$\mathbf{R}_{G\times I} = \begin{bmatrix} \frac{1}{F_1} & 0 & 0 \\ \frac{1}{F_1} & -\frac{\beta_{22}}{2\beta_{21}}\frac{1}{F_1} & -\frac{\beta_{23}}{2\beta_{21}}\frac{1}{F_1} \\ \frac{1}{F_1} & 0 & 0 \\ \frac{1}{F_1} & 0 & -\frac{\beta_{43}}{\beta_{41}}\frac{1}{F_1} \\ -\frac{\beta_{51}}{2\beta_{52}}\frac{1}{F_2} & \frac{1}{F_2} & -\frac{\beta_{53}}{2\beta_{52}}\frac{1}{F_2} \\ -\frac{\beta_{61}}{\beta_{62}}\frac{1}{F_2} & \frac{1}{F_2} & 0 \\ 0 & \frac{1}{F_2} & 0 \\ -\frac{\beta_{81}}{2\beta_{83}}\frac{1}{F_3} & -\frac{\beta_{82}}{2\beta_{83}}\frac{1}{F_3} & \frac{1}{F_3} \end{bmatrix} \tag{3.16}$$

Define $\boldsymbol{\gamma} \overset{\text{def}}{=} [\gamma_1, \gamma_2, ..., \gamma_G]'$which describes the expected value of goals, and the goal can be rewritten as

$$\boldsymbol{\gamma}_{G\times 1} = \mathbf{R}_{G\times I}\,\boldsymbol{\pi}_{I\times 1} \tag{3.17}$$

where $\boldsymbol{\pi} \overset{\text{def}}{=} [\pi_1, \pi_2, ..., \pi_I]'$ is an I-dimensional vector of firms' economic profits.

3.3.2 Contract Value

Let $\boldsymbol{\kappa} = [\kappa_1, \kappa_2, \cdots, \kappa_K]'$ be a K-dimensional vector with each scalar κ_k representing the expected value of a contract. Within each contract k, let ω_{kg} denote the weight of goal g, which is the percentage of contract value vested after goal g is achieved. Let A and R be the set of absolute and relative goals, respectively. Then, κ_k can be expressed as the weigted average of goal value

$$\kappa_k = \sum_g \gamma_g \omega_{kg} = \sum_{g\in A} \omega_{kg}\pi_i \frac{1}{F_i} + \sum_{g\in R} \omega_{kg}\left(\pi_i - \frac{1}{|\mathcal{P}_g|}\sum_j \frac{\beta_{gj}}{\beta_{gi}}\pi_j\right)\frac{1}{F_i}$$

For matrix notation, define a $K \times G$ matrix $\boldsymbol{\Omega}$, with (k, g) entry being ω_{kg}. Note that $\omega_{kg} = 0$ if goal g is not included in contract g. Then, the vector contract values $\boldsymbol{\kappa}$ reads

$$\boldsymbol{\kappa}_{K\times 1} = \boldsymbol{\Omega}_{K\times G}\,\boldsymbol{\gamma}_{G\times 1} \tag{3.18}$$

3.3.3 Executive Utility

Let y_k denote the notional value of a contract k. The utility of an executive m is the weighted average value of all her contracts: $u_m = \frac{\sum_{k\in\mathcal{K}(\mathcal{I},m)} \kappa_k y_k}{\sum_{k\in\mathcal{K}(\mathcal{I},m)} y_k}$, where $\mathcal{K}(\mathcal{I},m)$ is the set of contracts owned by manager m. Define an $M \times K$ matrix $\mathbf{\Psi}$, where each entry $\psi_{mk} \stackrel{\text{def}}{=} \frac{y_k}{\sum_{k\in\mathcal{K}(\mathcal{I},m)} y_k}$ is the reciprocal of the total value of manager m's contracts. Apparently, $\psi_{mk} = 0$ if contract k does not belong to manager m. Therefore, the utility vector of all the executives $\mathbf{u} \stackrel{\text{def}}{=} [u_1, u_2, ..., u_M]'$ is given by

$$\mathbf{u}_{M\times 1} \;=\; \mathbf{\Psi}_{M\times K}\, \boldsymbol{\kappa}_{K\times 1} \tag{3.19}$$

3.3.4 Value of the Pricing Manager

Let V_i be the objective function of firm i's pricing manager. Then, V_i can be written as the weighted average utility of all the exectuives at firm i: $V_i = \frac{\sum_{k\in\mathcal{K}(i,m)} y_k u_m}{\sum_{k\in\mathcal{K}(i,M)} y_k}$, where $\mathcal{K}(i,m)$ is the set of contracts signed by firm i and executive m, and $\mathcal{K}(i,M)$ is the set of contracts owned by firm i. Define an $I \times M$ matrix $\mathbf{\Lambda}$, where each entry $\lambda_{im} \stackrel{\text{def}}{=} \frac{\sum_{k\in\mathcal{K}(i,m)} y_k}{\sum_{k\in\mathcal{K}(i,M)} y_k}$ is the share of manager m's contract value at firm i out of the total value of all managerial contracts at firm i. Thus, the vector of pricing managers' objectives is

$$\mathbf{V}_{I\times 1} \;=\; \mathbf{\Lambda}_{I\times M}\, \mathbf{u}_{M\times 1} \tag{3.20}$$

It can also be expressed as a linear transformation of profits:

$$\mathbf{V}_{I\times 1} \;=\; \mathbf{\Lambda}_{I\times M}\mathbf{\Psi}_{M\times K}\mathbf{\Omega}_{K\times G}\mathbf{R}_{G\times I}\, \boldsymbol{\pi}_{I\times 1} \stackrel{\text{def}}{=} \mathbf{\Phi}_{I\times I}\boldsymbol{\pi}_{I\times 1} \tag{3.21}$$

Then, we do a normalization by defining $\mathbf{\Theta}_{I\times I} \stackrel{\text{def}}{=} \text{diag}^{-1}(\mathbf{\Phi})\,\mathbf{\Phi}$, or equivalently in scalar format, define $\theta_{ij} \stackrel{\text{def}}{=} \frac{\phi_{ij}}{\phi_{ii}}$, where ϕ_{ij} is the entry of matrix $\mathbf{\Phi}$. In this way, we can rewrite the objective function of firm i as

$$V_i \;\propto\; \pi_i + \sum_{j\neq i} \theta_{ij}\pi_j \tag{3.22}$$

We interpret θ_{ij} as the weight that the pricing manager of firm i assigns to the profits of firm j relative to its own profits. If firm i adopts RPE and takes firm j as a peer, then $\theta_{ij} < 0$, because the pricing manager of firm i wants to outperform the competitors to maximize her compensation. If firm i only values absolute performance (no RPE), or adopts RPE but does not benchmark against firm j, the weights $\theta_{ij} = 0, \forall\, j \neq i$. The weights θ_{ij} define a managerial incentive network over the set of Compustat firms. The value of θ_{ij} depends on the four matrices discussed above. In Cournot competition, firms maximize their objective function by choosing quantities according to

$$\frac{\partial V_i}{\partial q_i} \;=\; \frac{\partial \pi_i}{\partial q_i} + \sum_{j\neq i} \theta_{ij}\frac{\partial \pi_j}{\partial q_i} \tag{3.23}$$

3.4 Equilibrium and Counterfactual RPE scenarios

In the model, firms compete in an economy-wide Cournot oligopoly game, where the manager of each firm i maximizes the objective function V_i by choosing an optimal allocation $\mathbf{q}^{\mathbf{\Xi}}$. 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 given by

$$0 \;=\; (\mathbf{b} - \mathbf{c^0}) \;-\; (2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma} + \mathbf{\Theta} \circ \mathbf{\Sigma})\, \mathbf{q} \tag{3.24}$$

$$\text{where} \qquad \mathbf{\Delta} \;\stackrel{\text{def}}{=}\; \begin{bmatrix} \delta_1 & 0 & \cdots & 0 \\ 0 & \delta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_I \end{bmatrix} \tag{3.25}$$

is the matrix that represents firm-specific economies of scale. $\mathbf{\Sigma}$ and $\mathbf{\Theta}$ are the adjacency matrices of the networks of product rivalries[8] and RPE, respectively, and $\circ$ denotes the Hadamard (element-wise) product. $\mathbf{b}$ and $\mathbf{c^0}$ are the demand and supply function intercepts. Under the assumption that the matrix $(2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma} + \mathbf{\Theta} \circ \mathbf{\Sigma})$ is invertible, the Cournot RPE allocation $\mathbf{q}^{\mathbf{\Xi}}$ is given by

$$\mathbf{q}^{\Xi} \;=\; (2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma} + \mathbf{\Theta} \circ \mathbf{\Sigma})^{-1}(\mathbf{b} - \mathbf{c^0}) \tag{3.26}$$

To analyze the effects of RPE on firm behaviors and the aggregate economy, we would like to compare the RPE equilibrium to a counterfactual scenario in which firms maximize their own profits π_i as under standard Cournot competition. This amounts to solving the case where $\mathbf{\Theta}$ is a null matrix. The potential function and the optimal allocation (interior solution) in that case would be

$$\begin{aligned} \text{Cournot Potential}: \quad \Phi(\mathbf{q}) \quad &= \quad \mathbf{q}'(\mathbf{b} - \mathbf{c^0}) - \tfrac{\mathbf{1}}{\mathbf{2}}\mathbf{q}'\,(2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma})\,\mathbf{q} - F \\ \text{Cournot Allocation}: \quad \mathbf{q}^{\Phi} \quad &= \quad \arg\max_{\mathbf{q}} \Phi(\mathbf{q}) \;=\; (2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma})^{-1}(\mathbf{b} - \mathbf{c^0}) \end{aligned}$$

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, $\mathbf{\Theta}$.

- Strict-only counterfactual: This scenario applies counterfactual weights to firms with positive compensation tied to Strict RPE and zero compensation tied to Index-based RPE. We reallocate all of their executives' performance-based compensation to Strict RPE, removing the influence of absolute performance objectives on their decision-making. This adjustment yields a new matrix of RPE weights, $\mathbf{\Theta^S}$.
- Full counterfactual: This scenario extends to all firms that adopt any form of RPE. Here, all firms using relative performance evaluation are assumed to allocate their entire performance-based compensation to RPE objectives, eliminating any weight on absolute performance.

[8] The matrix of cosine similarities $\mathbf{\Sigma}$ defines an *undirected network*, which intuitively boils down to $\mathbf{\Sigma} = \mathbf{\Sigma}'$. This does not hold for the RPE network which implies a *directed network*.

This further intensifies the emphasis on pro-competitive behavior, resulting in a new matrix of RPE weights, $\mathbf{\Theta^F}$.

3.5 Identification 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.

3.5.1 Model Consistent Metrics

As it appears from equation 3.16 the sensitivities $\beta^{\mathcal{M}}$ of the performance metrics $\mathcal{M}$ to a change in profits π are a key ingredient to determine the importance of each objective within each contract summarized by the matrix $\mathbf{R}$. In turn, the matrix $\mathbf{R}$ is a crucial component in the construction of $\mathbf{\Theta}$, the matrix of firm to firm RPE weights and the central object of our model. In this paragraph we briefly explain how we compute the sensitivities $\beta^{\mathcal{M}}$ starting from the modeling assumption we make on the metrics.

As discussed in Section 3.3, in our model, all performance metrics take the form of a linear transformation of profits, leading to the following model representation of the metrics (for a generic goal g at firm i and time t): $\mathcal{M}_{git} = \beta^{\mathcal{M}}_{git}(\pi_{it} - f_{it}) + o_{it}$. It is straightforward to notice that the sensitivity of metric $\mathcal{M}_{git}$ to a change in profits is $\frac{\partial \mathcal{M}_{git}}{\partial \pi_{it}} = \beta^{\mathcal{M}}_{git}$[9], exactly the quantity we need to construct the entries in $\mathbf{R}$. Notice that this result hinges on the assumption that, as opposed to π_{it}, this sensitivity is exogenous and not a function of the equilibrium strategy profile $\mathbf{q}$[10]. This result, makes it clear that the sensitivities $\beta^{\mathcal{M}}_{git}$ provide a mapping between the (endogenous) realized profits and the metric chosen by the firm i for goal g in year t.

To make things more concrete, consider Return on Assets as the metric of interest such that we have $ROA_{git} = \frac{1}{FixedAssets_{it-1}} \cdot NetIncome_t$. Relating this equation with the model representation for performance metrics, $NetIncome_{it}$ would be proxied by $(\pi_{it} - f_{it})$[11] and β^{ROA}_{git} will be equal to $\frac{1}{FixedAssets_{it-1}}$ which can be computed directly from the firm's financial found in Compustat. We thus have found a way to compute β^{ROA}_{git} for *every firm* adopting Return on Assets as a metric for a certain goal. Following this reasoning, we compute the sensitivities $\beta^{\mathcal{M}}_{git}$ for all firms and metrics they adopt employing balance sheet data to approximate the original financial metrics as closely as possible.

3.5.2 Using Compensation Data to Identify $\mathbf{\Theta}$

This subsection illustrates how using our theory we can map to the data the matrices $\mathbf{\Lambda}$, $\mathbf{\Psi}$, $\mathbf{\Omega}$, $\mathbf{R}$ which are combined to obtain the adjacency matrix of peer relationships $\mathbf{\Theta}$. Here becomes crucial recalling the notional contract value we introduced in section 2.1.2.

[9] This implies the existence of one sensitivity for each firm and each metric in each year.

[10] If that were not the case the derivative $\frac{\partial \mathcal{M}_{git}}{\partial \pi_{it}}$ would be a more complex object. Since the model is static, we can only compute metrics based on past (i.e., predetermined) balance sheet values and current-period profits, excluding forward-looking components commonly used in financial performance measures (e.g. the stock price).

[11] Which is not involved in the computation of the RPE weights.

- A generic entry $\lambda_{im} \overset{\text{def}}{=} \frac{\sum_{k \in \mathcal{K}(i,m)} y_k}{\sum_{k \in \mathcal{K}(i,M)} y_k}$ of $\mathbf{\Lambda}$, represents the relative importance of each executive m to its firm i, and is computed as the sum of notional contract values of manager m over the sum of the notional contract values that firm i has in place.
- a generic entry $\psi_{mk} \overset{\text{def}}{=} \frac{y_k}{\sum_{k \in \mathcal{K}(\mathcal{I},m)} y_k}$ of $\mathbf{\Psi}$, represents the relative importance of each contract k to its manager m, and is computed as the notional contract value y_k over the sum of the notional contract values for manager m.
- A generic entry $\omega_{kg} \overset{\text{def}}{=} \frac{y_k \cdot percentVest_{kg} \cdot expansionFactor_{kg}}{\sum_{g \in G(\mathcal{I},k)} y_k \cdot percentVest_{kg} \cdot expansionFactor_{kg}}$ of $\mathbf{\Omega}$, represents the relative importance of each goal g to its contract k, and is computed as the notional contract value y_k multiplied by its weight within the contract ($percentVest_{kg}$) and by a scaling factor ($expansionFactor_{kg}$) we use to account for the fact that each goal might have a performance period spanning multiple years. We invite the reader interested in how we deal with the time dimension of the contracts to consult Appendix B.1.1.
- $\mathbf{R}$, contains the weights assigned by the pricing manager of each firm adopting RPE to all firms as detailed in Section 3.3. The entries are a function of the firms fixed costs F_i and metrics' sensitivities $\beta_{it}^{\mathcal{M}}$ of the firms to profits. We identify the entries using the *ppent* (property plant and equipment) which we use to compute the fixed costs F_i and other firms accounting and financial measures. The reasoning behind the computation of $\beta_{it}^{\mathcal{M}}$ was explained in the previous section. These are all available in Compustat. The current mapping used to observe the metric sensitivities $\beta_{it}^{\mathcal{M}}$ from balance sheet concepts can be found in Appendix A.1.

3.5.3 Identification

All of the unobserved variables in the model are identified subject to two parameters: α, the degree of horizontal differentiation between goods; and $\mathbf{\Delta}$, the scale matrix. We will first show how to identify the remaining variables conditional on these two parameters and then we will illustrate our procedure for obtaining α and $\mathbf{\Delta}$.

Similar to Ederer and Pellegrino [2025], we express the vector of firm profits π and fixed costs $\mathbf{f}$ in terms of the quantity vector $\mathbf{q}$ and the matrices $\mathbf{\Delta}$, $\mathbf{\Sigma}$, and $\mathbf{\Theta}$, and find the $\mathbf{q}$ that satisfied the following equation:

$$\pi + \mathbf{d} = \mathbf{diag}(\mathbf{q})(\mathbf{I} + \frac{1}{2}\mathbf{\Delta} + \mathbf{\Theta} \circ \mathbf{\Sigma})\,\mathbf{q} \tag{3.27}$$

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

$$p_i \;=\; \frac{p_i q_i}{q_i} \qquad \text{and} \qquad c_i^0 \;=\; \frac{\text{TVC}_i}{q_i} - \frac{\delta_i}{2} q_i \tag{3.28}$$

Then, we derive the demand intercept b_i as:

$$\mathbf{b} \;=\; (2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma} + \mathbf{\Theta} \circ \mathbf{\Sigma})\,\mathbf{q} + \mathbf{c}^0 \tag{3.29}$$

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

Assumption 1. *There are as many common characteristics as words – i.e.* $\mathbf{v}_i$ *and* $\mathbf{a}_i$ *are both vectors in* $\mathbb{R}^m$.

Assumption 2. *$\forall\, i$, the vectors $\mathbf{a}_i$ and $\mathbf{v}_i$ are collinear up to a permutation – that is $\mathbf{a}_i = \mathbb{P}\mathbf{v}_i\mathscr{C}_i$ for some $m \times m$ permutation matrix $\mathbb{P}$ and some strictly-positive scalar $\mathscr{C}_i$.*

These assumptions allow us to proxy word frequencies in 10-K product descriptions ($\mathbf{v}_i$) for product characteristics loadings ($\mathbf{a}_i$) where a vector of word frequencies $\mathbf{v}_i \in \mathbb{R}^{61146}$ is

$$\mathbf{v}_i = \begin{bmatrix} v_{i,1} \\ v_{i,2} \\ \vdots \\ v_{i,61146} \end{bmatrix} \tag{3.30}$$

and normalizing it by its Euclidean norm we obtain the vector $\mathbf{a_i}$:

$$\mathbf{a_i} \overset{\text{def}}{=} \frac{\mathbf{v}_i}{\|\mathbf{v}_i\|} \tag{3.31}$$

This guarantees that any dot product $\mathbf{a_i'a_j}$ results in a number between 0 and 1.

Finally, the HP cosine similarity between any firm pair in the economy is succintly described by the following matrix product:

$$\mathbf{A'A} = \begin{bmatrix} \mathbf{a}_1'\mathbf{a}_1 & \mathbf{a}_1'\mathbf{a}_2 & \dots & \mathbf{a}_1'\mathbf{a}_I \\ \mathbf{a}_2'\mathbf{a}_1 & \mathbf{a}_2'\mathbf{a}_2 & \dots & \mathbf{a}_2'\mathbf{a}_I \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_I'\mathbf{a}_1 & \mathbf{a}_I'\mathbf{a}_2 & \dots & \mathbf{a}_I'\mathbf{a}_I \end{bmatrix} \tag{3.32}$$

We direct the interested reader to Ederer and Pellegrino [2025] who provide a more thorough discussion and rich empirical validations of these assumptions.

The last step is to identify the scalar parameter α. Following the methodology in Pellegrino [2025]Ederer and Pellegrino [2025] and Nevo [2001], Goeree [2008], we obtain a closed-form expression of α as a function of the inverse cross-price elasticity of demand and other observables:

$$\alpha = -\frac{\epsilon_{ij}p_iq_j + \epsilon_{ji}p_jq_i}{2\cos_{ij}^{\text{HP}}\sqrt{p_iq_i - \text{TVC}_i}\sqrt{p_jq_j - \text{TVC}_j}} \tag{3.33}$$

where $\cos_{ij}^{\text{HP}}$ is the HP cosine similarity between firm i and firm j, and

$$\epsilon_{ij} = \frac{\partial \log p_i}{\partial \log q_j} = -\frac{q_j}{p_i}\sigma_{ij} \tag{3.34}$$

is the inverse cross-price demand elasticity. Using the inverse cross-price elasticity between Kellogg's and Quaker Oats from Nevo [2001], we obtain $\alpha = 0.12$, which pins down all other parameters of our model.

3.5.4 Validation

In this paragraph we briefly describe the validation procedures of the GHL block of the model. The first two are of qualitative nature, the third is quantitative. For a more complete discussion of

Figure 3: Network of Peer Relationships

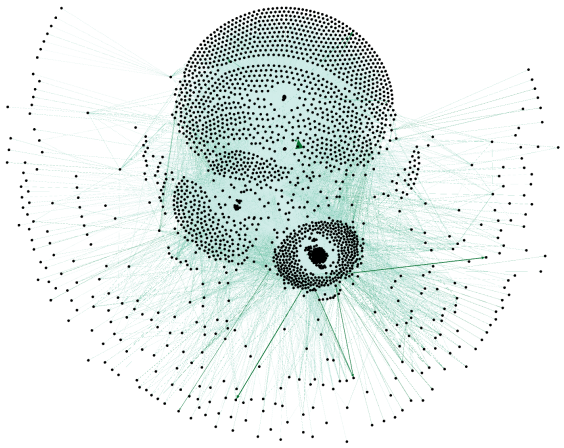


FIGURE NOTES: The plot represents the full network of peer relationships in year 2016 that emerges from our theory of firm level incentives. There are 2241 nodes and more than 100,000 edges. To generate this plot we apply in sequence the OpenOrd algorithm of Martin et al. [2011] and the gravity algorithm introduced by Fruchterman and Reingold [1991].

the validation of the GHL, the reader is invited to consult Pellegrino [2025] who devised a careful validation in three steps:

- **Clusters in the Product Space.** The first one is a visualization of the community structure that characterizes the similarity data from Hoberg and Phillips [2016]. This structure is shown to closely match the GICS classifications associated with the firms but it also shows that such classifications are somehow arbitrary. Thinking of the product space as a fuzzy space accomodates the degree of differentation in firms' products.
- **Self-Reported Competitors.** This exercise is a proof of the general validity of the HP data but cannot be taken as a. This is why it is important to also point the reader to the second validation step that comes directly from Hoberg and Phillips [2016], who leverage 10-K forms to identify the self-reported closest rivals of each publicly listed firm appearing in their data. They show that their similarity data generates more accurate predictions about rivalries than the traditional industry classifications.
- **Demand Estimates.** The third one compares the sign and magnitude of the GHL cross-price elasticities with those estimated in leading studies in the industrial organization literature (Berry et al. [1993], Nevo [2001], Goeree [2008]) for firm pairs who also appear in HP.

Table 1: Variable Definitions and Mapping to Compustat

Panel A: Observed Variables

Notation	Description	Measurement	Source
$p_i q_i$	Revenues	Revenues	Compustat
TVC_i	Total Variable Costs	Costs of Goods Sold	Compustat
f_i	Stochastic Fixed Costs	Selling, General and Administrative Costs	Compustat
F_i	Upper Bound Fixed Cost Distribution	Property, Plant and Equipment	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, β_j $\forall j \neq i$, Number of peers	ISS Incentive Lab

Panel B: Identified Variables and Parameters

Notation	Description	Identification
δ_i	Marginal Cost Slope	$= 0$ in the baseline model
α	Utility Weight on Common Characteristics	$= 0.12$ using Nevo [2001] as in Pellegrino [2025], Ederer and Pellegrino [2025]
q_i	Output	$\mathbf{q}$ such that $\pi + \mathbf{d} = \mathbf{diag}(\mathbf{q})(\mathbf{I} + \frac{1}{2}\mathbf{\Delta} + \mathbf{\Theta} \circ \mathbf{\Sigma})\,\mathbf{q}$
c_i^0	Marginal Cost Intercept	$= \frac{h_i}{q_i} - \frac{1}{2}\delta_i q_i$
$(\mathbf{I} + \mathbf{\Sigma})$	$\partial \mathbf{p}/\partial \mathbf{q}$	$= (1-\alpha)\mathbf{I} + \alpha \mathbf{A}'\mathbf{A}$
$\mathbf{b}$	Demand Intercept	$= (2\mathbf{I} + \mathbf{\Delta} + \mathbf{\Sigma} + \mathbf{\Theta} \circ \mathbf{\Sigma})\,\mathbf{q} + \mathbf{c^0}$

Figure 4: Product Similarity and RPE Weights

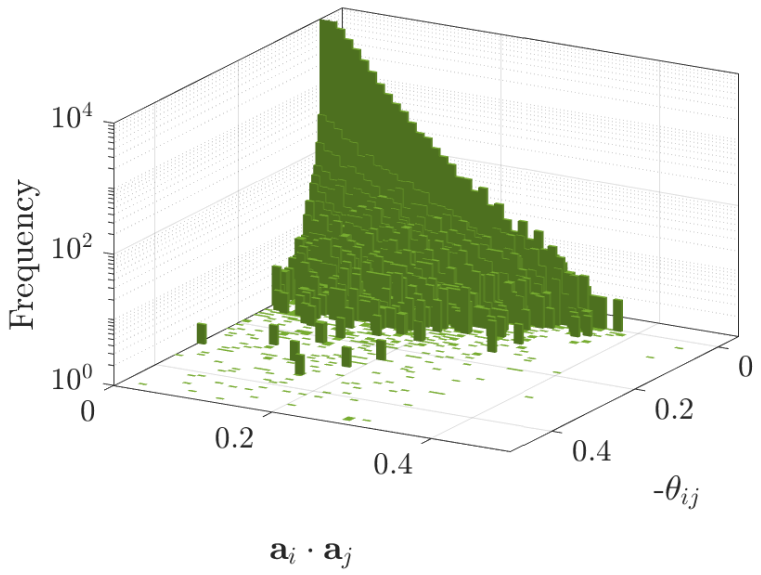


FIGURE NOTES: The 3D plot displays the joint distribution of product similarities computed by Hoberg and Phillips [2016] and the peer weights that emerge from our theory of firm level incentives.

4 Results and Analysis

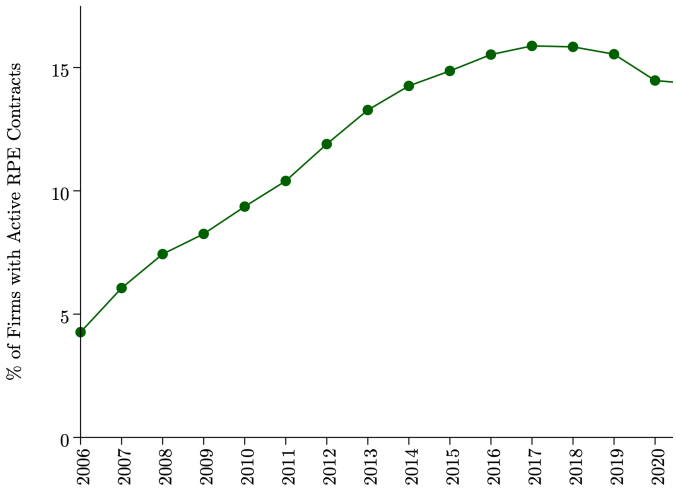
After we have provided a thorough discussion of the institutional details and the theory we now discuss the key findings from data and our model.

4.1 Product Similarity and RPE

This section examines the structure of peer relationships and the adoption of RPE across firms, highlighting the interaction with the product market. Figure 3 provides a comprehensive representation of the full network of peer relationships across firms. The nodes in the graph represent individual firms, while the edges illustrate the connections determined by RPE benchmarking practices. The figure displays the heterogeneity in RPE adoption: the varying thickness of the edges reflects the intensity of peer relationships, where thicker edges denote stronger peer benchmarking. Figure 4 depicts the joint distribution of product similarity and RPE peer weights across firm-pairs in our sample. While the majority of observations cluster near zero on both axes—signaling that many pairs neither share closely overlapping product lines nor specifically benchmark against each other's performance—there is a noticeable "ridge" where higher similarity aligns with stronger (more negative) peer weights. This finding suggests that firms offering closely related products tend to adopt stricter RPE measures against one another, reinforcing the model's implication that pro-competitive effects concentrate most intensely among direct rivals who penalize each other's underperformance.

Figure 5: Extensive and Intensive Margin Adoption of RPE

(a) RPE Adoption on the Extensive Margin



(b) Distribution of Strict RPE Intensity, 2006 vs 2021

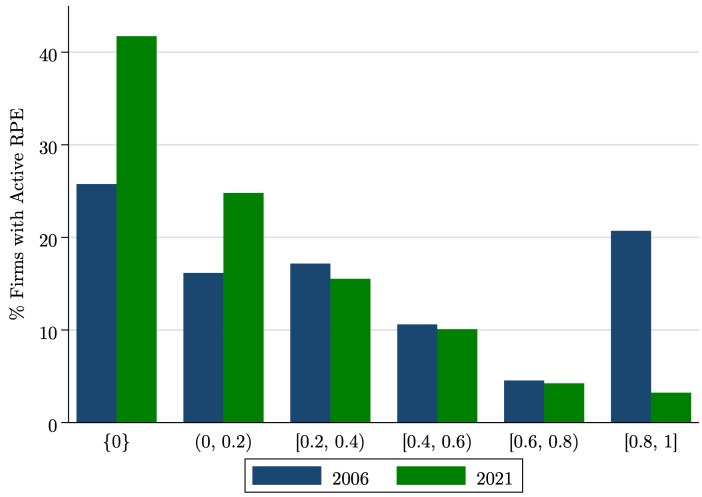


FIGURE NOTES: This graph illustrates RPE adoption on both the extensive and intensive margins. Panel (a) depicts the share of firms with active RPE contracts in our sample from 2006 to 2021. Panel (b) presents the distribution of firms by Strict RPE intensity for the years 2006 and 2021. Strict RPE intensity is measured as the proportion of a firm's total compensation allocated to Strict RPE. The bin {0} represents firms with no Strict RPE adoption, and the bin (0, 0.2) includes firms where the Strict RPE intensity falls between 0 and 0.2, and so on.

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

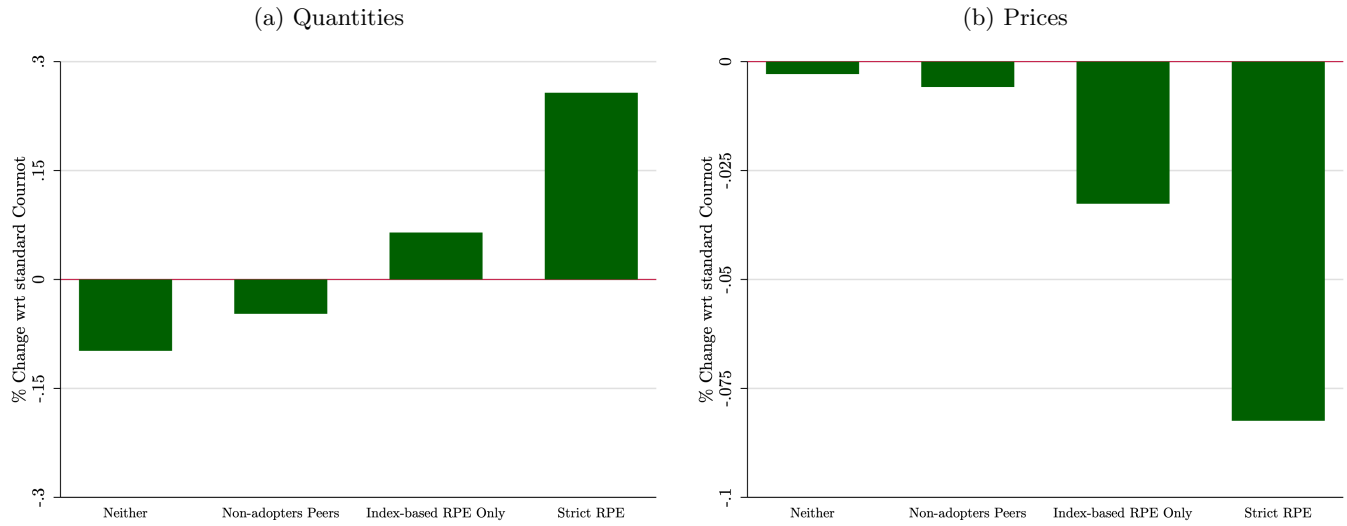


FIGURE NOTES: The graphs display the percentage change in quantities, Panel (a), and prices, Panel (b), under the RPE allocation aggregated by RPE group, relative to the standard Cournot allocation (no RPE).

4.2 Extensive vs Intensive Margin of RPE Adoption

Over time, there has been a clear upward trend in the adoption of RPE in the executive compensation contracts. As Panel (a) of Figure 5 shows, only about 3% of firms[12] in 2006 had active RPE contracts, but this number steadily increased to around 15% in 2020s, which indiates that RPE has become an increasingly common component of executive compensation over time. However, while adoption has increased, the intensity of RPE usage within firms remains relatively low. Panel (b) of Figure 5 plots a histogram of firms over Strict RPE intensity, measured by the share of compensation tied to Strict RPE, for the year 2006 and 2021. Although more firms in 2021 adopt RPE than in 2006, the majority fall into the lower-intensity categories, with more than 40% of RPE adopters adopting only index-based RPE, and another 25% assigning less than 20% of compensation to Strict RPE. This suggests that while firms are increasingly incorporating RPE, they tend to use it in a limited capacity rather than as a dominant component of executive pay.

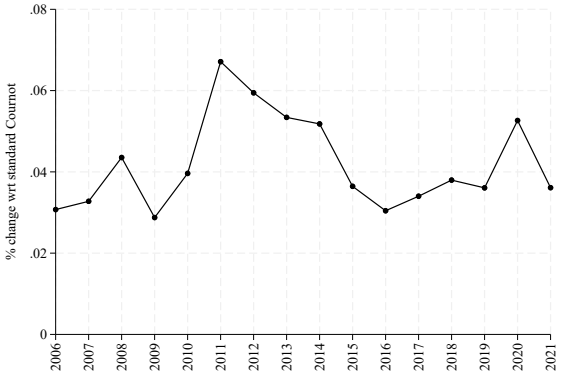
To further investigate the implications of RPE adoption, we analyze changes in quantities and prices across different groups of firms, categorized by their RPE practices. In this regard we identify four different groups:

- Adopters who are further split in two sub-groups:
  - Strict RPE Adopters: firms who adopt at least one Strict RPE contract.
  - Index-based RPE Adopters: firms who adopt RPE in Index-based mode only.
- Non-Adopter Peers: contains firms who are target to RPE contracts but do not adopt RPE.
- Neither: Firms that are neither RPE adopters nor peers.

[12]The share of RPE adoption presented here is a lower bound of RPE adoption, due to the limited coverage of ISS. The ISS only covers about a quarter of publicly-listed US firms in Compustat.

Figure 7: RPE Equilibrium vs. Standard Cournot: Welfare and Distributional Effects

(a) Change in Welfare



(b) Change in CS and Firm Profits

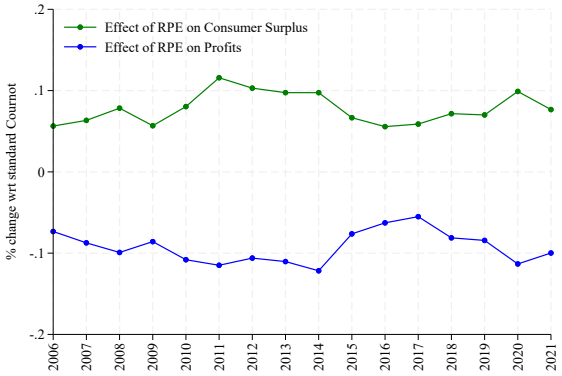


FIGURE NOTES: Panel (a) of the figure plots the percentage changes in total welfare in RPE equilibrium relative to the standard Cournot from 2006 to 2021. Panel (b) plots the percentage changes in firm profits and consumer surplus in RPE equilibrium compared to the standard Cournot from 2006 to 2021.

Panel (a) in Figure 6 illustrates the percentage change in output quantities for the four groups in 2016. Firms adopting Strict RPE exclusively exhibit the largest increase in output, highlighting the pro-competitive effects of benchmarking against a custom group of peers. Conversely, groups not adopting RPE (Neither and Non-adopter Peers) show marginal declines in output. Panel (b) in Figure 6 shows the percentage change in prices across four groups in 2016. Prices decrease across the board, with firms using Strict RPE experiencing the most significant price reductions. These findings suggest that Strict RPE intensifies competitive pressures and leads to lower prices. In contrast, the Neither and Non-adopter Peers groups show minimal price adjustments, reflecting their limited exposure to competitive benchmarking.

4.3 Welfare Analysis

Next, we study time trends in welfare using annual estimates derived from applying our model to Compustat data. Our primary focus is on understanding the effects of RPE adoption on firm behaviors and welfare among publicly listed U.S. companies from 2006 to 2021. Our analysis accounts for changes in product offerings and RPE over time by incorporating time-varying data on both product similarity and managerial incentives.

4.3.1 Analysis of the Aggregate Economy

Comparison: RPE Equilibrium vs. Standard Cournot. Figure 7 displays the welfare implications of RPE and its evolutions over time. In the left panel, we plot the percentage change of total welfare in RPE equilibrium relative to the standard Cournot benchmark, which fluctuates between 0.03% and 0.07% from 2006 to 2021. Though modest in magnitude, the consistently positive values throughout the period indicate a pro-competitive effect of RPE. Notably, the efficiency gains do not follow a steady upward trend despite a dramatic increase of the number of firms adopting RPE over the period.

Figure 8: RPE Equilibrium vs. Standard Cournot: Firm Strategies

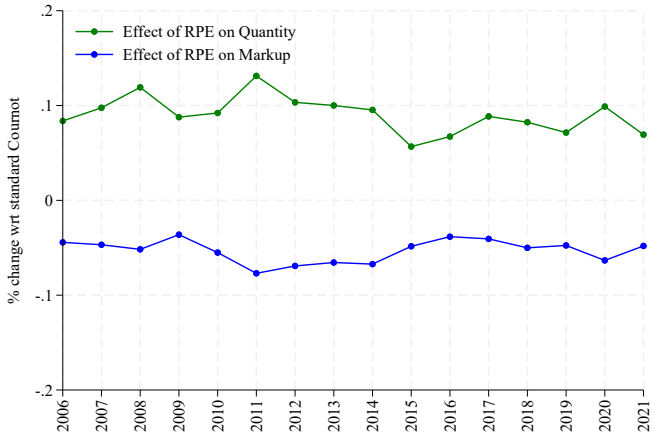


FIGURE NOTES: The graph displays the percentage changes in firm strategies in RPE equilibrium relative to the standard Cournot from 2006 to 2021. The green and blue curves plot the evolution of the weighted-average changes in firm quantities and markups in RPE economy compared to Cournot.

From an antitrust perspective, we are particularly interested in how much of the welfare gains can be attributed to firm profits and consumer surplus. The panel (b) of Figure 7 displays the relative changes of the two components compared to the standard Cournot. RPE has increased consumer surplus by around 0.1% and at the same time decreased corporate profits by around 0.1%. Although the rise in consumer surplus is comparable to the decline in corporate profits, its leads to an overal increase in total welfare, because corporate profits accounted for only around one-fifth of total surplus.

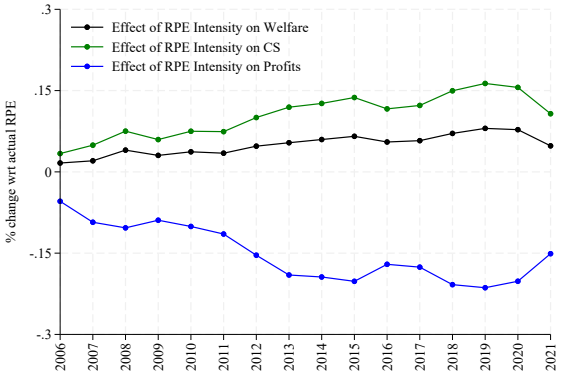
RPE adoption also influence firm behaviors. Figure 8 plots the weighted-average changes in firm quantities and markups. For each individual firm, we first calculate the percentage change in quantity and markup under RPE economy relative to the Cournot economy, then take the average weighted by revenues. Firms generally compete more aggressively compared to the Cournot benchmark: quantities increase by an average of 0.09%, while markups decline by 0.06%, and the effects remain quite stable over time.

Comparison: Full RPE Counterfactual vs. Actual RPE. In Section 4.2, we show that although a growing number of firms adopt RPE on the extensive margin, most adopters assign only minimal weight to relative performance against a defined group of peer firms. To further assess the potential effects of RPE, we examine the Full RPE counterfactual where all RPE-adopting firms shift to a scenario where 100% of executive compensation is tied to relative performance. This exercise allows us to isolate the impact of RPE intensity on competition, firm behavior, and overall welfare without changing the set of RPE adopters.

Figure 9 shows the results, with panel (a) showing welfare effects and panel (b) depicting firm strategies. Compared to actual RPE equilibrium, welfare in the counterfactual scenario further increases at a steady rate over time, rising from 0.02% in 2006 to 0.05% in 2021. Relative to the

Figure 9: Full RPE Counterfactual vs. Actual RPE: Welfare Effects and Firm Strategies

(a) Change in Welfare, Profits, and CS



(b) Average Change in Quantity and Markup

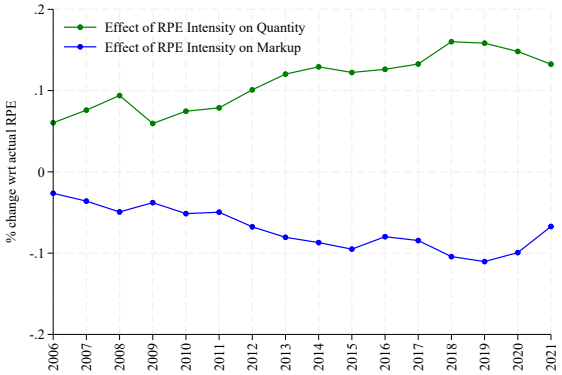


FIGURE NOTES: The graph plots the percentage changes of welfare effects and firms strategies in **Full RPE counterfactual** equilibrium compared to **actual RPE** equilibrium. Panel (a) plots the evolution of relative changes in total welfare (black curve), consumer surplus (blue curve), and corporate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

standard Cournot benchmark, this represents an increase from 0.05% in 2006 to approximately 0.1% in 2021. Breaking it down, the relative change in consumer surplus steadily grows from 0.03% to more than 0.1%, while the change in firm profits decline from -0.05% to -0.2%. The stronger emphasis on relative performance intensifies competitive pressures, leading firms to expand output and lower prices more aggressively than in the actual RPE equilibrium, as shown in panel (b). These findings suggest that while the current adoption of RPE has modestly enhanced competition, a stronger reliance on relative peer benchmarking could further amplify pro-competitive effects, benefiting consumers through lower markups and increased quantities.

4.3.2 Analysis by Group

To better understand the heterogeneous effects of RPE, we group firms into RPE adopters and non-adopters. Note that some Compustat firms may adopt RPE but are not recorded in the ISS data set, requiring us to classify them as non-adopters. Still, we use the following results to shed light on the heterogeneous effects of RPE across firms.

Both firms adopting and not adopting RPE see a decline in profits compared to Cournot. However, RPE adopters (green curve) face only a moderate reduction in profits over time, with relatively stable fluctuations ranging between 0.05%-0.1%. The non-adopters (blue curve), on the other hand, experience a more pronounced and consistent decline in profits, with a sharp drop reaching nearly -0.25% between 2018 and 2020. This suggests that while RPE reduces profit margins overall, it redistributes competitive advantages toward adopters. A possible reason is that adopters tend to be larger firms, as noted in Section B.2. Compared to them, In contrast, non-adopters - often smaller firms with less market power - suffer greater profit declines due to higher competitive pressures and limited strategic flexibility.

In Figure 11 we further examine the effects of RPE on quantity produced and markup. Firms

Figure 10: RPE Equilibrium vs. Standard Cournot: Change in Firm Profits by Group

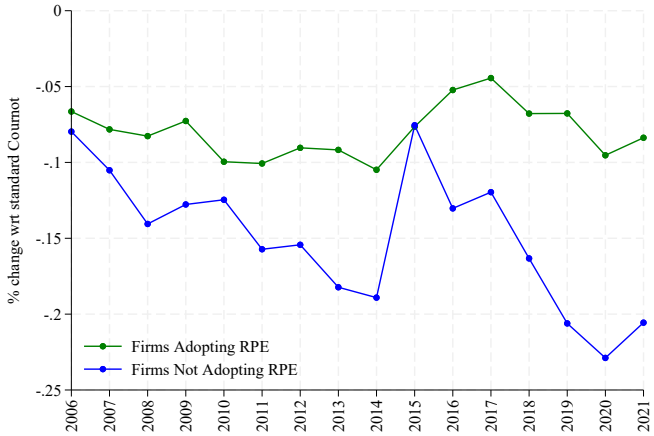
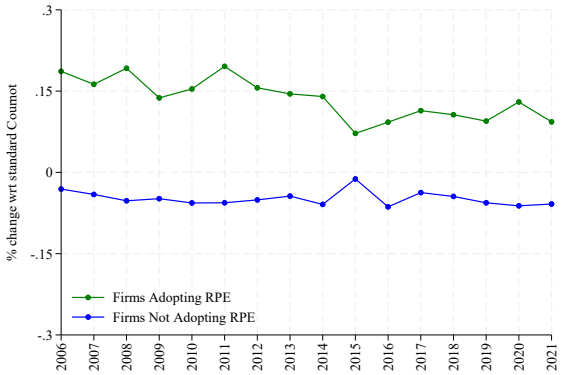


FIGURE NOTES: The graph displays the percentage changes in firm profits by group in RPE equilibrium relative to the standard Cournot from 2006 to 2021. The green and blue curves plot the changes for RPE adopters and non-adopters, respectively.

adopting RPE expand their output over time by around 0.15%, while non-adopters slightly reduce their output by 0.05%. This aligns with the observed consumer surplus gains and suggests that RPE incentivizes firms to compete more aggressively by increasing production. On the other hand, markups decline more sharply for RPE adopters, reinforcing the idea that relative performance benchmarking leads to price competition and lower profit margins. Non-adopting firms experience relatively stable markups but at the cost of reduced output, further highlighting the competitive disadvantage they face.

Figure 11: RPE Equilibrium vs. Standard Cournot: Firm Strategies by Group

(a) Change in Quantity by Group



(b) Change in Markup by Group

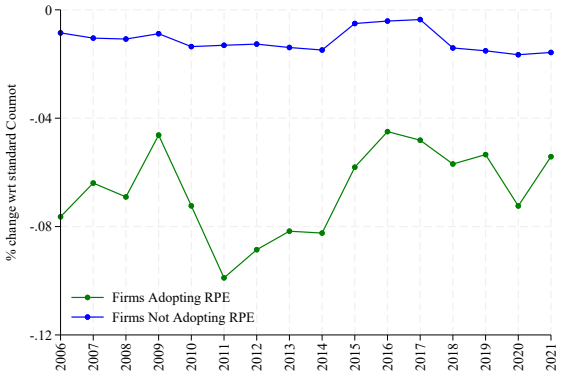


FIGURE NOTES: The graph displays the percentage changes in quantities and markups by group in RPE equilibrium relative to the standard Cournot from 2006 to 2021. Panel (a) and (b) plot the changes in quantity and price, respectively. The green and blue curves plot the changes for firms adopting RPE and not adopting RPE, respectively.

Figure 12: Full RPE counterfactual vs. Actual RPE: Firm Profits by Group

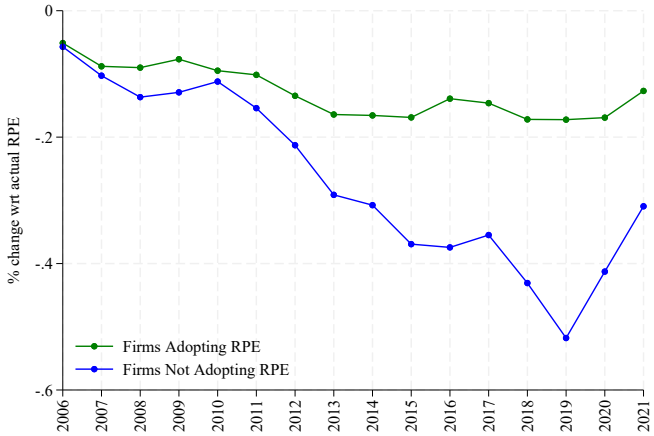


FIGURE NOTES: The graph plots the percentage changes of welfare by group in **Full RPE counterfactual** equilibrium compared to **actual RPE** equilibrium. The green and blue curves plot the evolution for RPE adopters and non-adopters, respectively.

In Figure 11, we examine how RPE affects output and markups, complementing the above profit analysis. Firms adopting RPE (green curve) expand their output over time by approximately 0.15%, while non-adopters (blue curve) slightly reduce theirs by around 0.05%. This aligns suggests that RPE brings more aggressive competition through increased production. On the other hand, markups decline more sharply for RPE adopters, which suggests that RPE leads to price competition and lower profit margins. In contrast, non-adopters maintain relatively stable markups but at the cost of reduced output, reflecting their competitive disadvantage.

We also run the Full RPE counterfactual on the two groups. The results, depicted in Figure 12, show that both adopters and non-adopters experience steeper profit declines relative to the actual RPE equilibrium, confirming that higher RPE intensity generate more competition. Adopters see their profits decline from approximately -0.15% in 2006 to around -0.2% by 2021, a sharper drop than in the actual RPE setting. Non-adopters, already at a disadvantage, suffer an even greater decline, with profits falling from -0.15% in 2006 to nearly -0.5% in 2021, reinforcing the redistribution of comparative advantages to adopters. Additional counterfactual analyses on output and markups, presented in the Appendix, further support these findings, showing that greater RPE intensity amplifies differences in performance across firms.

5 Conclusion

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: gross 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)[13].

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.
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

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

Table 2: Taxonomy of Relative Performance Metrics 1/2

Metric in the data	correct	Formula	Imputed Sensitivity	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 spread 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	$GP_t - OE_t - D_t - A_t$	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 3: 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%
Gross 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%

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 The Time Dimension of Contracts

The contract information reported in proxy material represents ex-ante information on incentive plans. In the raw version of GPBA each contract occupies one row and the observations are at the *fiscal year-firm-executive-contract-objective* level. The fiscal year variable reports the year in which the grant was awarded, yet it is not informative about the performance period which is the period of time over which performance is assessed. This is why, to correctly account for managerial incentives, it is necessary to construct a panel at the *year-firm-executive-contract-objective* level (and no longer Fiscal Year). The data from ISS provides two key variables to achieve the desired data structure, *vestLow* and *vestHigh*. These represent respectively the beginning and the end of the *performance period*[14], expressed in months from the date at which the grant is signed. Thanks to these variables we are able to perform what we call an *expansion* of the original version of the dataset to obtain the complete ex-ante representation of the contracts.

As an example, consider an obective represented by a single row in the data, with the following characteristics:

$$grantDate = 01/06/2010 \text{ (DD/MM/YYYY)}$$
$$vestLow = \text{-}2$$
$$vestHigh = 34$$

We know that the manager's compensation depends on the performance of the firm between the 1st of April 2010 and the 1st of April 2013. We use this information to obtain one observation for each year that is part of the performance period. In this case the contract will cover year 2010 for 8 months, years 2011 and 2012 fully, and year 2013 for the first 4 months. Because each goal has a notional monetary value attached to it, we need to make an assumption about how the manager values each unit of time in which the contract is active. We postulate that the manager weighs

[14]The performance period defined as the span of time through which the performance is assessed. It can change across different objectives within the same contract.

equally each unit of time, implying that the weight that each year receives is given by the notional value of the objective, divided by the length of the performance periods in months and multiplied by the number of months for which the objective is active in the year. Using our running example, let us say that the notional value of the objective is M. We know that the performance period lasts 36 months. This implies the following notional values for the objective in the different years:

$$\text{Year 2010: } m_{2010} = M \cdot \tfrac{8}{36}$$
$$\text{Year 2011: } m_{2011} = M \cdot \tfrac{12}{36}$$
$$\text{Year 2012: } m_{2012} = M \cdot \tfrac{12}{36}$$
$$\text{Year 2013: } m_{2013} = M \cdot \tfrac{4}{36}$$

We call *expansion factor* the number that attributes a share of the goal to each year If a contract involves more that one goal, before we take the *notional contract valu*e and multiply it by *percentVest.* Doing this attributes the desired relative importance to each of the two objectives within a contract. After this step, the *expansion* procedure we have seen is applied to every objective.

Having constructed a panel at the *year-firm-executive-contract-objective* level, we now know the notional value of each goal within a year. This is the notional contract value, y_k, we use to bring the model to the data.

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 and growing over time. Figure 13 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.

Figure 13: Relative share of performance based compensation 2006 vs 2021, by Sector

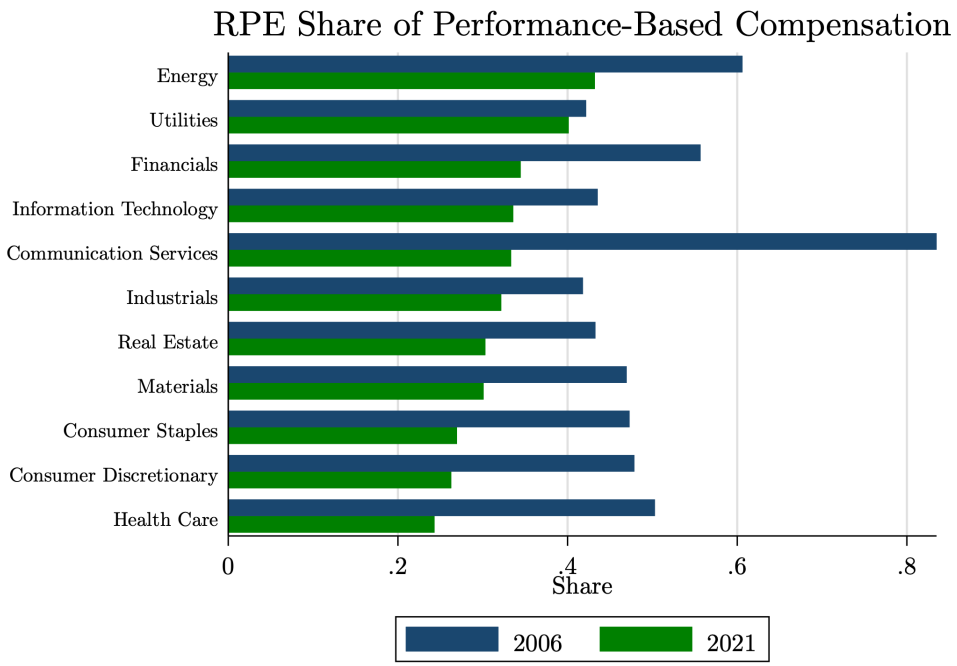


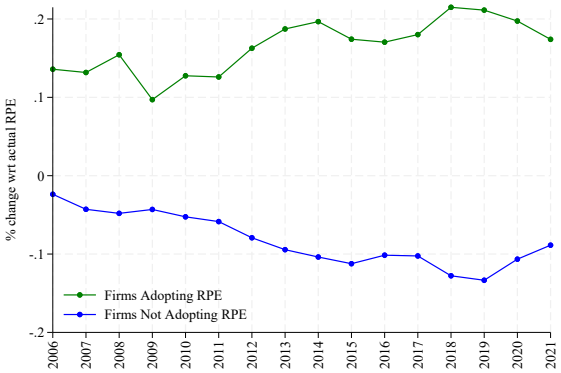
FIGURE NOTES: The figure reports the share of performance based compensation that is allocated to relative objectives as opposed to absolute objectives in each sector for the years 2006 and 2021. The sectors follow the GICS classification at the sector level.

- 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.

C Figures

Figure 14: Full RPE Counterfactual vs. Actual RPE: Firm Strategies by Group

(a) Change in Quantity by Group



(b) Change in Markup by Group

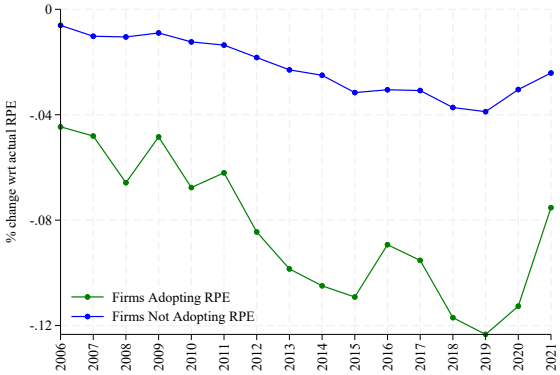


FIGURE NOTES: The graph displays the percentage changes in quantities and markups by group in Full RPE counterfactual relative to the actual RPE from 2006 to 2021. Panel (a) and (b) plot the changes in quantity and price, respectively. The green and blue curve plot the changes for firms adopting RPE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

Figure 15: Network Visualization of the Hoberg-Phillips Dataset

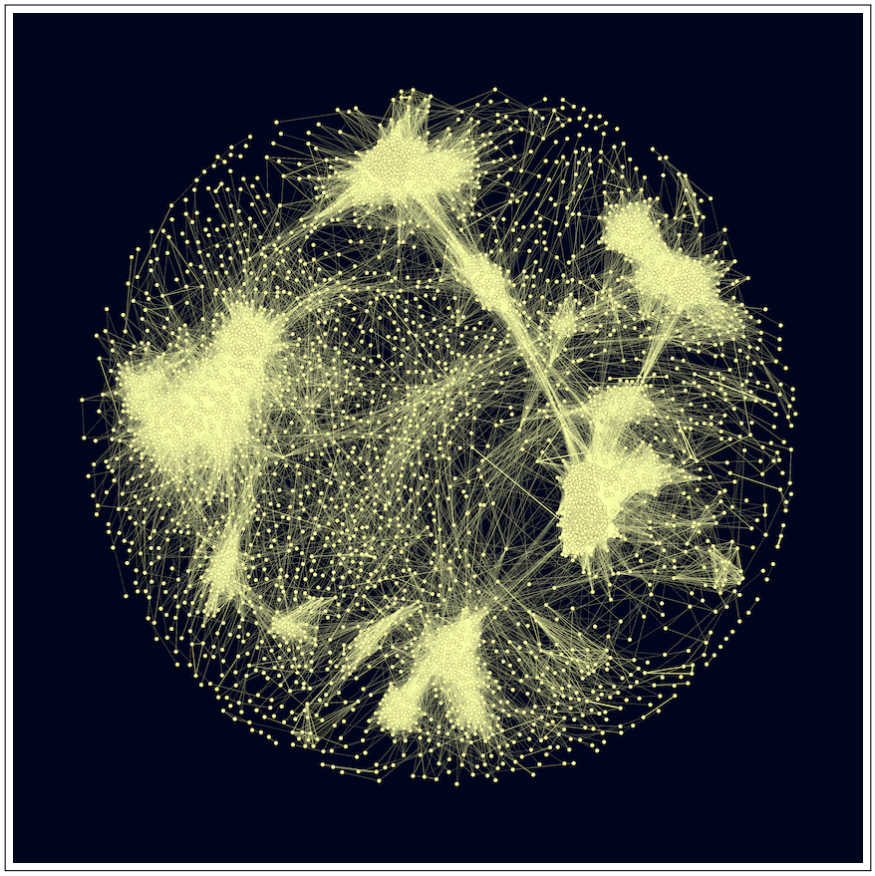


FIGURE NOTES: The following diagram is a two-dimensional representation of the network of product similarities computed by Hoberg and Phillips [2016], which is used in the estimation of the model presented in Section 3. The data covers the universe of Compustat firms in 2004. Firm pairs that have thicker links are closer in the product market space. These distances are computed in a space that has approximately 61,000 dimensions. To plot this high-dimensional object over a plane, I applied the gravity algorithm of Fruchterman and Reingold [1991], which is standard in social network analysis.