R&D Networks: Theory, Empirics and Policy Implications☆

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Abstract

We analyze a model of R&D alliance networks where firms are engaged in R&D collaborations that lower their production costs while competing on the product market. We provide a complete characterization of the Nash equilibrium and determine the optimal

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R&D subsidy program that maximizes total welfare. We then structurally estimate this model using a unique panel of R&D collaborations and annual company reports. We use our estimates to study the impact of targeted vs. non-discriminatory R&D subsidy policies and empirically rank firms according to the welfare-maximizing subsidies they should receive.
Key words: R&D networks, innovation, spillovers, optimal subsidies, industrial policy
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1. Introduction

R&D collaborations have become a widespread phenomenon especially in industries with a rapid technological development such as the pharmaceutical, chemical and computer industries [cf. Hagedoorn, 2002]. Through such collaborations firms generate R&D spillovers not only to their direct collaboration partners but also indirectly to other firms that are connected to them within a complex network of R&D collaborations. At the same time an increasing number of countries have resorted to various financial policies to stimulate R&D investments by private firms [cf. e.g. Czarnitzki et al., 2007]. In particular, OECD countries spend more than 50 billion dollars per year on such R&D policies [cf. Takalo et al., 2017], including direct R&D subsidies and R&D tax credits. The aim of this paper is to develop and structurally estimate an R&D network model and to empirically evaluate different R&D subsidy policies that take spillovers in R&D networks into account.

In particular, we consider a general model of competition à la Cournot where firms choose both, their R&D expenditures and output levels. Firms can reduce their costs of production by exerting R&D efforts. We characterize the Nash equilibrium of this game for any type of R&D collaboration network as well as for any type of competition structure between firms (Proposition 1). We show that there exists a key trade-off faced by firms between the *technology (or knowledge) spillover effect* of R&D collaborations and the *product rivalry effect* of competition. The former effect captures the *positive* impact of R&D collaborations on output and profit while the latter captures the *negative* impact of competition and market stealing effects.

Due to the existence of externalities through technology spillovers and competition effects that are not internalized in the R&D decisions of firms, the social benefits of R&D differ from the private returns of R&D. This creates an environment where government funding programs that aim at fostering firms' R&D activities can be welfare improving. We analyze the optimal design of such R&D subsidy programs (where a planner can subsidize a firm's R&D effort) that take into account the network externalities in our model. We derive an exact formula for any type of network and competition structure that determines the optimal amount of subsidies per unit of R&D effort that should be given to each firm. We discriminate between homogeneous subsidies (Proposition 2), where each firm obtains the same amount of subsidy per unit of R&D effort and targeted subsidies (Proposition 3), where subsidies can be firm specific.

We then bring the model to the data by using a unique panel of R&D collaborations and annual company reports over different sectors, regions and years. We adopt an instrumental variable (IV) strategy to estimate the best-response function implied by the theoretical model to identify the *technology (or knowledge) spillover effect* of R&D collaborations and the *product rivalry effect* of competition in a panel data model with both firm and time fixed effects. In particular, following Bloom et al. [2013], we use changes in the firm-specific tax price of R&D to construct IVs for R&D expenditures. Furthermore, to address the potential endogeneity of R&D networks, we use predicted R&D networks based on predetermined dyadic characteristics to construct IVs to identify the casual effect of R&D spillovers. As predicted by the theoretical model, we find that the spillover effect has a *positive* and significant impact on output and profit while the competition effect has a *negative* and significant impact.

Using our estimates and following our theoretical results, we then empirically determine the optimal subsidy policy, both for the homogenous case where all firms receive the same subsidy per unit of R&D effort, and for the targeted case, where the subsidy per unit of R&D effort may vary across firms. The targeted subsidy program turns out to have a much higher impact on total welfare as it can improve welfare by up to 80%, while the homogeneous subsidies can improve total welfare only by up to 4%. We then empirically rank firms according to the welfare-maximizing subsidies that they receive by the planner. We find that the firms that should be subsidized the most are not necessarily the ones that have the highest market share, the largest number of patents or the most central position in the R&D network. Indeed, these measures can only partially explain the ranking of firms that we find, as the market share is more related to the product market rivalry effect, while the R&D network and the patent stocks are more related to the technology spillover effect, and both effects are incorporated in the design of the optimal subsidy program.

The rest of the paper is organized as follows. In Section 2, we compare our contribution to the existing literature. In Section 3, we develop our theoretical model, characterize the Nash equilibrium of this game, and define the total welfare. Section 4 discusses optimal R&D subsidies. Section 5 describes the data. Section 6 is divided into four parts. In Section 6.1, we define the econometric specification of our model while, in Section 6.2, we highlight our identification strategy. The estimation results are given in Section 6.3. Section 6.4 provides a robustness check. The policy results of our empirical analysis are given in Section 7. We discuss our main assumptions in Section 8. Finally, Section 9 concludes. In the Online Appendix, we provide the proofs of the propositions (Appendix A), introduce the network definitions and characterizations used throughout the paper (Appendix B), highlight the contribution of our model with respect to the literature on games on networks (Appendix C), discuss the Herfindahl concentration index (Appendix D), perform an analysis in terms of Bertrand competition instead of Cournot competition (Appendix E), provide a theoretical model of direct and indirect technology spillovers (Appendix F), determine market failures due to technological externalities that are not internalized by the firms and investigate the optimal network structure of R&D collaborations (Appendix G), give a detailed description of how we construct and combine our different datasets for the empirical analysis (Appendix H), provide a numerical algorithm for computing optimal subsidies (Appendix I) and, finally, provide some additional robustness checks for the empirical analysis (Appendix J).

2. Related Literature

Our theoretical model analyzes a game with strategic complementarities where firms decide about production and R&D effort by treating the network as exogenously given. Thus, it belongs to a particular class of games known as *games on networks* [cf. Jackson and Zenou, 2015].[1] Compared to this literature, we develop an R&D network model where competition between firms is explicitly modeled, not only within the same product market but also across different product markets (see Proposition 1). We also provide an explicit welfare characterization and perform a policy analysis of R&D subsidies.

In the industrial organization literature, there is a long tradition of models that analyze product and price competition with R&D collaborations (see, e.g. D'Aspremont and Jacquemin [1988]). The first paper that provides an explicit analysis of R&D networks is that by Goyal and Moraga-Gonzalez [2001]. The authors introduce a strategic Cournot oligopoly game in the presence of externalities induced by a network of R&D collaborations. Even though we do not study network formation as in Goyal and Moraga-Gonzalez [2001], we are able to provide results for all possible networks with an arbitrary number of firms and a complete characterization of equilibrium output and R&D effort choices in multiple interdependent markets.

From an econometric perspective, there has been recently a significant progress in the literature on identification and estimation of social network models (see Chandrasekhar [2016], for a recent survey). One of the most popular models in applied research is the linear social network models. Bramoullé et al. [2009] provide identification conditions for this model based on the intransitivities in the network structure and propose an IV-based estimation strategy exploiting exogenous characteristics of indirect connections. Yet, the validity of the IVs relies on the assumption that the network structure captured by the

[1] The economics of networks is a growing field. For recent surveys of the literature, see Jackson [2008] and Jackson et al. [2017].

adjacency matrix is exogenous. If the adjacency matrix depends on some unobserved variables that are correlated with the error term of the social interaction regression, then the adjacency matrix is endogenous and this IV-based estimator would be inconsistent. In this paper, taking advantage of the panel data structure in the empirical analysis, we introduce both firm and time fixed effects into the linear social network model to attenuate the potential asymptotic bias caused by the endogenous adjacency matrix. To further reduce this potential bias, we use the predicted adjacency matrix based on predetermined dyadic characteristics (instead of the observed adjacency matrix) to construct IVs for this model. This allows us to estimate the causal impact of R&D spillovers.

There is a large empirical literature on technology spillovers [see e.g. Bloom et al., 2013], and R&D collaborations [see e.g. Hanaki et al., 2010]. There is also an extensive literature that estimates the effect of R&D subsidies on private R&D investments and other measures of innovative performance (see e.g. Bloom et al. [2002], and, for a survey, see Klette et al. [2000]). However, to the best of our knowledge, our paper is the first that provides a ranking of firms according to the welfare maximizing subsidies that they should receive.

3. Theoretical Framework

3.1. Network Game

We consider a general Cournot oligopoly game where a set of firms $\mathcal{N} = \{1, \dots, n\}$ is partitioned in $M \geq 1$ heterogeneous product markets $\mathcal{M}_m$, $m = 1, \dots, M$. Let $|\mathcal{M}_m|$ denote the size of market $\mathcal{M}_m$. We allow for consumption goods to be imperfect substitutes (and thus differentiated products) by adopting the consumer utility maximization approach of Singh and Vives [1984]. We first consider q_i the demand for the good produced by firm i in market $\mathcal{M}_m$. A representative consumer in market $\mathcal{M}_m$ obtains the following gross utility from consumption of the goods $\{q_i\}_{i\in\mathcal{M}_m}$

$$\bar{U}_m(\{q_i\}_{i\in\mathcal{M}_m}) = \alpha_m \sum_{i\in\mathcal{M}_m} q_i - \frac{1}{2}\sum_{i\in\mathcal{M}_m} q_i^2 - \frac{\rho}{2}\sum_{i\in\mathcal{M}_m}\sum_{j\in\mathcal{M}_m, j\neq i} q_i q_j.$$

In this formulation, the parameter α_m captures the heterogeneity in market sizes, whereas $\rho \in [0,1)$ measures the degree of substitutability between products. In particular, $\rho \to 1$ depicts a market of perfectly substitutable goods, while $\rho = 0$ represents the case of local monopolies. The consumer maximizes net utility $U_m = \bar{U}_m - \sum_{i \in \mathcal{M}_m} p_i q_i$, where p_i is the price of good i. This gives the inverse demand function for firm i

$$p_i = \bar{\alpha}_i - q_i - \rho \sum_{j \in \mathcal{M}_m, j \neq i} q_j, \tag{1}$$

where $\bar{\alpha}_i = \sum_{m=1}^{M} \alpha_m \mathbb{1}_{\{i \in \mathcal{M}_m\}}$. In the model, we will study both the general case where $\rho > 0$ but also the special case where $\rho = 0$. The latter case is when firms are local monopolists so that the price of the good produced by each firm i is only determined by its own quantity q_i (and the size of the market) but not by the quantities of other firms, i.e. $p_i = \bar{\alpha}_i - q_i$.

Firms can reduce their production costs by investing in R&D as well as by benefiting from an R&D collaboration with another firm. The amount of this cost reduction depends on the R&D effort e_i of firm i and the R&D efforts of the R&D collaboration partners of firm i. Given the effort level e_i, the marginal cost c_i of firm i is given by:[2]

$$c_i = \bar{c}_i - e_i - \varphi \sum_{j=1}^{n} a_{ij} e_j, \tag{2}$$

The network of R&D collaborations, G, can be represented by a symmetric $n \times n$ *adjacency matrix* $\mathbf{A}$. Its elements $a_{ij} \in \{0,1\}$ indicate whether there exists a link between nodes i and j.[3] In the context of our model, $a_{ij} = 1$ if firms i and j have an R&D collaboration and $a_{ij} = 0$ otherwise. As a normalization, we set $a_{ii} = 0$. In Equation (2), the total cost reduction for firm i stems from its own research effort e_i and the research effort of all other collaborating firms (via *knowledge spillovers*), which is captured by the term

[2]We assume that the R&D effort independent marginal cost $\bar{c}_i$ is large enough such that marginal costs, c_i, are always positive for all firms $i \in \mathcal{N}$.

[3]See Online Appendix B.1 for definitions and characterizations of networks.

$\sum_{j=1}^{n} a_{ij}e_j$, where $\varphi \geq 0$ is the marginal cost reduction due to a collaborator's R&D effort. We assume that R&D effort is costly. In particular, the cost of R&D effort is given by $\frac{1}{2}e_i^2$, which is increasing in effort and exhibits decreasing returns. Firm i's profit is then given by

$$\pi_i = (p_i - c_i)q_i - \frac{1}{2}e_i^2. \tag{3}$$

Inserting the inverse demand from Equation (1) and the marginal cost from Equation (2) into Equation (3) gives the following strictly quasi-concave profit function for firm i

$$\pi_i = (\bar{\alpha}_i - \bar{c}_i)q_i - q_i^2 - \rho \sum_{j=1}^{n} b_{ij}q_iq_j + q_ie_i + \varphi q_i \sum_{j=1}^{n} a_{ij}e_j - \frac{1}{2}e_i^2, \tag{4}$$

where $b_{ij} = 1$ if firms i and j operate in the same market and $b_{ij} = 0$ otherwise. Consequently, the market structure can be represented by an $n \times n$ competition matrix $\mathbf{B} = [b_{ij}]$. If we arrange firms by markets they operate in, the competition matrix $\mathbf{B}$ will be a block diagonal matrix with a zero diagonal and blocks of sizes $|\mathcal{M}_m|$, $m = 1, \ldots, M$.

3.2. Nash Equilibrium

We consider quantity competition among firms à la Cournot.[4] The following proposition establishes the Nash equilibrium where each firm i simultaneously chooses *both* its output q_i and R&D effort e_i in an arbitrary network of R&D collaborations represented by the adjacency matrix $\mathbf{A}$ and an arbitrary market structure represented by the competition matrix $\mathbf{B}$. Throughout the paper, denote by $\mathbf{I}$ the $n \times n$ identity matrix, $\boldsymbol{\iota}$ the $n \times 1$ vector of ones, and $\lambda_{\max}(\mathbf{A})$ the largest eigenvalue of $\mathbf{A}$. Denote by $\mu_i \equiv \bar{\alpha}_i - \bar{c}_i$ for all $i \in \mathcal{N}$, and $\boldsymbol{\mu}$ the corresponding $n \times 1$ vector with components μ_i. Denote also by $\underline{\mu} = \min_i \{\mu_i \mid i \in \mathcal{N}\}$ and $\overline{\mu} = \max_i \{\mu_i \mid i \in \mathcal{N}\}$, with $0 < \underline{\mu} \leq \overline{\mu}$. Finally, denote by $\mathbf{b}_{\boldsymbol{\mu}}(G, \phi) \equiv (\mathbf{I} - \phi\mathbf{A})^{-1}\boldsymbol{\mu}$ the vector of $\boldsymbol{\mu}$-weighted Katz-Bonacich centralities, and

[4] In Online Appendix E, we show that the same functional forms for best response quantities and efforts can be obtained for price setting firms under Bertrand competition as we find them in the case of Cournot competition.

$\mathbf{b}_{\boldsymbol{\iota}}(G,\phi) \equiv (\mathbf{I}-\phi\mathbf{A})^{-1}\boldsymbol{\iota}$ the vector of unweighted Katz-Bonacich centralities, where $\phi = \varphi/(1-\rho)$. [5]

Proposition 1. *Consider the n-player simultaneous-move game with the payoff given by Equation (4), where $\varphi \geq 0$, $0 \leq \rho < 1$ and $0 < \underline{\mu} \leq \mu_i \equiv \bar{\alpha}_i - \bar{c}_i \leq \overline{\mu}$.*

(i) If $\varphi = 0$ or

$$\varphi\lambda_{\max}(\mathbf{A}) + \rho \max_{m=1,\dots,M}\{|\mathcal{M}_m|-1\} < 1 \tag{5}$$

then there exists a unique Nash equilibrium with the equilibrium R&D efforts $\mathbf{e}^*$ and outputs $\mathbf{q}^*$ given by

$$\mathbf{e}^* = \mathbf{q}^* = (\mathbf{I}-\varphi\mathbf{A}+\rho\mathbf{B})^{-1}\boldsymbol{\mu}. \tag{6}$$

and the equilibrium profits π_i^* given by

$$\pi_i^* = \frac{1}{2}(q_i^*)^2, \quad \forall i \in \mathcal{N}. \tag{7}$$

(ii) If $\phi \equiv \varphi/(1-\rho) < \lambda_{\max}(\mathbf{A})^{-1}$, then there exists a unique Nash equilibrium in the case that all firms operate in a single market (i.e., $M = 1$), with the equilibrium R&D efforts $\underline{\mathbf{e}}^*$ and outputs $\underline{\mathbf{q}}^*$ given by

$$\underline{\mathbf{e}}^* = \underline{\mathbf{q}}^* = \frac{1}{1-\rho}\left(\mathbf{b}_{\boldsymbol{\mu}}(G,\phi) - \frac{\rho\,\|\mathbf{b}_{\boldsymbol{\mu}}(G,\phi)\|_1}{(1-\rho)+\rho\,\|\mathbf{b}_{\boldsymbol{\iota}}(G,\phi)\|_1}\mathbf{b}_{\boldsymbol{\iota}}(G,\phi)\right). \tag{8}$$

In addition, if

$$\phi\lambda_{\max}(\mathbf{A}) + \frac{n\rho}{1-\rho}\left(\frac{\overline{\mu}}{\underline{\mu}}-1\right) < 1 \tag{9}$$

then, $\underline{\mathbf{e}}^* = \underline{\mathbf{q}}^* > \mathbf{0}$.

(iii) If $\varphi < \lambda_{\max}(\mathbf{A})^{-1}$, then there exists a unique Nash equilibrium in the case that goods are non-substitutable (i.e., $\rho = 0$), with the equilibrium R&D efforts $\overline{\mathbf{e}}^*$ and outputs $\overline{\mathbf{q}}^*$ given by $\overline{\mathbf{e}}^* = \overline{\mathbf{q}}^* = \mathbf{b}_{\boldsymbol{\mu}}(G,\varphi) = (\mathbf{I}-\varphi\mathbf{A})^{-1}\boldsymbol{\mu} > \mathbf{0}$.

[5] The proof of Proposition 1 is given in Online Appendix A. See the Online Appendix B.3 for a precise definition of the Bonacich centrality used in the proposition.

(iv) If the conditions stated in (i)-(iii) hold, then $\overline{\mathbf{q}}^* \geq \mathbf{q}^* \geq \underline{\mathbf{q}}^* > \mathbf{0}$*, where* $\mathbf{q}^*$ *is the vector of equilibrium outputs in the general case given by Equation (6).*

Proposition 1 (i) characterizes the Nash equilibrium for the most general case with a general R&D network and product market structure, while (ii) and (iii) characterize the equilibria of two special cases, namely, the case where all firms operate in the same market and the case where goods are non-substitutable, which provide the lower and upper bounds for the equilibrium in the general case as shown in (iv).

The first-order condition of profit maximization with respect to the R&D effort leads to $e_i = q_i$, while the first-order condition with respect to the output leads to

$$q_i = \mu_i + \varphi \sum_{j=1}^{n} a_{ij} q_j - \rho \sum_{j=1}^{n} b_{ij} q_j, \tag{10}$$

or, in matrix form, $\mathbf{q} = \boldsymbol{\mu} + \varphi \mathbf{A}\mathbf{q} - \rho \mathbf{B}\mathbf{q}$. If $\varphi = 0$ and $0 \leq \rho < 1$, or if the condition given by Equation (5) holds, the matrix $\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B}$ is positive definite, and thus there exists a unique Nash equilibrium characterized by Equation (6). This result generalizes those of Ballester et al. [2006], Calvó-Armengol et al. [2009] and Bramoullé et al. [2014] to allow agents to make multivariate choices on R&D effort and output levels in the presence of both network effects and competition effects.[6]

The key insight of Proposition 1 is the interaction between the *network effect*, through the adjacency matrix $\mathbf{A}$, and the *market effect*, through the competition matrix $\mathbf{B}$, and this is why the first-order condition with respect to q_i given by Equation (10) takes both of them into account.

[6]In the Online Appendix C, we highlight the contribution of our model with respect to the literature on games on networks by, first, shutting the network effects, second, the competition effects, and then comparing our model to that of Ballester et al. [2006] and Bramoullé et al. [2014].

3.3. Welfare

We next turn to analyzing welfare in the economy. Inserting the inverse demand from Equation (1) into net utility U_m of the consumer in market $\mathcal{M}_m$ shows that

$$U_m = \frac{1}{2}\sum_{i\in\mathcal{M}_m} q_i^2 + \frac{\rho}{2}\sum_{i\in\mathcal{M}_m}\sum_{j\in\mathcal{M}_m, j\neq i} q_i q_j.$$

The total consumer surplus is then given by $U = \sum_{m=1}^{M} U_m$. The producer surplus is given by aggregate profits $\Pi = \sum_{i=1}^{n} \pi_i$. As a result, the total welfare is equal to $W = U + \Pi$. Inserting profits as a function of equilibrium outputs from Equation (7) leads to the total welfare in the Nash equilibrium given by

$$W = \sum_{i=1}^{n}(q_i^*)^2 + \frac{\rho}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij} q_i^* q_j^* = \mathbf{q}^{*\top}\mathbf{q}^* + \frac{\rho}{2}\mathbf{q}^{*\top}\mathbf{B}\mathbf{q}^*. \tag{11}$$

As welfare in Equation (11) is increasing in the output levels of the firms, it is clear that the higher the production levels of the firms, the higher is welfare.[7]

4. R&D Subsidy Policies

Because of the externalities generated by R&D activities, market resource allocation will typically not be socially optimal. In Online Appendix G.1, we show that, indeed, there is a generic problem of under-investment in R&D, as the *private* returns from R&D are lower than the *social* returns from R&D. A policy intervention can correct this market failure through R&D subsidy or tax programs. We extend our framework by considering an optimal R&D subsidy program that reduces the firms' R&D costs. For our analysis, we first assume that all firms obtain a homogeneous subsidy per unit of R&D effort spent. Then, we proceed by allowing the social planner to differentiate between firms

[7] A discussion of how welfare is affected by the network structure can be found in the Online Appendix G.2. In particular, we investigate which network structure maximizes welfare.

and implement firm-specific R&D subsidies.[8]

4.1. Homogeneous R&D Subsidies

Following Spencer and Brander [1983], an government (or planner) is introduced that can provide a subsidy, $s \in [0, \bar{s}]$ per unit of R&D effort for some $\bar{s} > 0$. It is assumed that each firm receives the same per unit R&D subsidy. With a homogeneous R&D subsidy, the profit of firm i given by Equation (4) becomes:

$$\pi_i = (\bar{\alpha}_i - \bar{c}_i)q_i - q_i^2 - \rho q_i \sum_{j=1}^{n} b_{ij} q_j + q_i e_i + \varphi q_i \sum_{j=1}^{n} a_{ij} e_j - \frac{1}{2} e_i^2 + s e_i. \tag{12}$$

The game consists of two stages. In the first stage, the planner sets a subsidy rate on R&D effort, and in the second stage, the firms choose outputs and R&D efforts given the subsidy rate set in the first stage. The optimal R&D subsidy s^* determined by the planner is found by maximizing the total welfare $W(G, s)$ less the cost of the subsidy $s \sum_{i=1}^{n} e_i$, taking into account the fact that firms choose outputs and R&D efforts for a given subsidy rate by maximizing profits in Equation (12). If we define the net welfare as $\overline{W}(G, s) \equiv W(G, s) - s \sum_{i=1}^{n} e_i$, the social planner's problem is then given by

$$s^* = \arg\max_{s \in [0, \bar{s}]} \overline{W}(G, s).$$

Proposition 2. *Consider the n-player simultaneous-move game with the payoff given by Equation (12), where $\varphi \geq 0$, $0 \leq \rho < 1$ and $0 < \underline{\mu} \leq \mu_i \equiv \bar{\alpha}_i - \bar{c}_i \leq \overline{\mu}$. Let $\mathbf{R} = (\mathbf{I} - \varphi \mathbf{A} + \rho \mathbf{B})^{-1}(\mathbf{I} + \varphi \mathbf{A})$ and $\mathbf{H} = \mathbf{I} + \mathbf{R} + \mathbf{R}^\top - 2\mathbf{R}^\top \mathbf{R} - \rho \mathbf{R}^\top \mathbf{B} \mathbf{R}$.*

(i) If $\varphi = 0$ or the condition given by Equation (5) holds, then there exists a unique Nash

[8] We would like to emphasize that, as we have normalized the cost of R&D to one in the profit function of Equation (3), the absolute values of R&D subsidies are not meaningful in the subsequent analysis, but rather relative comparisons across firms are.

equilibrium with the equilibrium outputs given by

$$\mathbf{q}^* = (\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B})^{-1}\boldsymbol{\mu} + s\mathbf{R}\boldsymbol{\iota}, \tag{13}$$

the equilibrium R&D efforts given by

$$e_i^* = q_i^* + s, \quad \forall i \in \mathcal{N}, \tag{14}$$

and the equilibrium profits given by

$$\pi_i^* = \frac{(q_i^*)^2 + s^2}{2}, \quad \forall i \in \mathcal{N}. \tag{15}$$

(ii) If $\boldsymbol{\iota}^\top \mathbf{H}\boldsymbol{\iota} > 0$, *the optimal subsidy level is given by*

$$s^* = \frac{\boldsymbol{\iota}^\top(2\mathbf{R} + \rho\mathbf{B}\mathbf{R} - \mathbf{I})^\top(\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B})^{-1}\boldsymbol{\mu}}{\boldsymbol{\iota}^\top\mathbf{H}\boldsymbol{\iota}}, \tag{16}$$

provided that $0 < s^* < \bar{s}$.

In part (i) of Proposition 2, we solve the second stage of the game where firms decide their outputs and R&D efforts given the homogenous subsidy s. In part (ii) of the proposition, we solve the first stage of the game where the planner optimally determines the subsidy rate.

4.2. Targeted R&D Subsidies

We now consider the case where the planner can offer different subsidy rates to different firms, so that firm i, for all $i = 1, \ldots, n$, receives a subsidy $s_i \in [0, \bar{s}]$ per unit of R&D effort. Let $\mathbf{s}$ be an $n \times 1$ vector with components s_i. With target R&D subsidies, the profit of firm i given by Equation (4) becomes:

$$\pi_i = (\bar{\alpha}_i - \bar{c}_i)q_i - q_i^2 - \rho q_i \sum_{j=1}^n b_{ij}q_j + q_i e_i + \varphi q_i \sum_{j=1}^n a_{ij}e_j - \frac{1}{2}e_i^2 + s_i e_i. \tag{17}$$

If we define the net welfare as $\overline{W}(G,\mathbf{s}) \equiv W(G,\mathbf{s}) - \sum_{i=1}^{n} e_i s_i$, then the solution to the social planner's problem is given by

$$\mathbf{s}^* = \arg\max_{\mathbf{s}\in[0,\bar{s}]^n} \overline{W}(G,\mathbf{s}).$$

Proposition 3. *Consider the n-player simultaneous-move game with the payoff given by Equation (17), where $\varphi \geq 0$, $0 \leq \rho < 1$ and $0 < \underline{\mu} \leq \mu_i \equiv \bar{\alpha}_i - \bar{c}_i \leq \overline{\mu}$. Let $\mathbf{R} = (\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B})^{-1}(\mathbf{I} + \varphi\mathbf{A})$ and $\mathbf{H} = \mathbf{I} + \mathbf{R} + \mathbf{R}^\top - 2\mathbf{R}^\top\mathbf{R} - \rho\mathbf{R}^\top\mathbf{B}\mathbf{R}$.*

(i) If $\varphi = 0$ or the condition given by Equation (5) holds, then there exists a unique Nash equilibrium with the equilibrium outputs given by

$$\mathbf{q}^* = (\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B})^{-1}\boldsymbol{\mu} + \mathbf{R}\mathbf{s}, \tag{18}$$

the equilibrium R&D efforts given by

$$\mathbf{e}^* = \mathbf{q}^* + \mathbf{s}, \tag{19}$$

and the equilibrium profits given by

$$\pi_i^* = \frac{(q_i^*)^2 + s_i^2}{2}, \quad \forall i \in \mathcal{N}. \tag{20}$$

(ii) If the matrix $\mathbf{H}$ is positive definite, the optimal subsidy levels are given by

$$\mathbf{s}^* = \mathbf{H}^{-1}(2\mathbf{R} + \rho\mathbf{B}\mathbf{R} - \mathbf{I})^\top(\mathbf{I} - \varphi\mathbf{A} + \rho\mathbf{B})^{-1}\boldsymbol{\mu}, \tag{21}$$

provided that $0 < s_i^* < \bar{s}$ for all $i = 1, \ldots, n$.

This proposition provides us with an exact value of the targeted subsidy that needs to be given to each firm in order to maximize total (net) welfare.

5. Data

To obtain a comprehensive picture of R&D alliances, we use data on interfirm R&D collaborations stemming from two sources that have been widely used in the literature [cf. Schilling, 2009]. The first one is the Cooperative Agreements and Technology Indicators (CATI) database [cf. Hagedoorn, 2002]. This database only records agreements for which a combined innovative activity or an exchange of technology is at least part of the agreement. The second source is the Thomson Securities Data Company (SDC) alliance database. SDC collects data from the U.S. Securities and Exchange Commission (SEC) filings (and their international counterparts), trade publications, wires, and news sources. We include only alliances from SDC that are classified explicitly as R&D collaborations. The Online Appendix H.1 provides more information about the different R&D collaboration databases used for this study.

We then merged the CATI database with the Thomson SDC alliance database. For the matching of firms across datasets we used the name matching algorithm developed as part of the NBER patent data project [Atalay et al., 2011; Trajtenberg et al., 2009].[9] The merged datasets allow us to study patterns in R&D partnerships in several industries over an extended period of several decades. Observe that because of our IV strategy (See Section 6.2.3 below), which is based on R&D tax credits in the U.S., we only consider U.S. firms as in Bloom et al. [2013].

The systematic collection of inter-firm alliances started in 1987 and ended in 2006 for the CATI database. However, information about alliances prior to 1987 is available in both databases, and we use all information available starting from the year 1963 and ending in 2006. We construct the R&D alliance network by assuming that an alliance lasts 5 years. In the Online Appendix (Section J.1), we conduct robustness checks with different specifications of alliance durations.

Some firms might be acquired by other firms due to mergers and acquisitions (M&A) over time, and this will impact the R&D collaboration network [cf. e.g. Hanaki et al.,

[9]See https://sites.google.com/site/patentdataproject.

2010]. We account for M&A activities by assuming that an acquiring firm inherits all the R&D collaborations of the target firm. We use two complementary data sources to obtain comprehensive information about M&As. The first is the Thomson Reuters' SDC M&A database, which has historically been the reference database for empirical research in the field of M&As. The second database for M&As is Bureau van Dijk's Zephyr database, which is an alternative to the SDC M&As database. A comparison and more detailed discussion of the two M&As databases can be found in the Online Appendix H.2.

The combined CATI-SDC database provides the names for each firm in an alliance, but does not contain balance sheet information. We thus matched the firms' names in the CATI-SDC database with the firms' names in Standard & Poor's Compustat U.S. annual fundamentals database, as well as Bureau van Dijk's Osiris database, to obtain information about their balance sheets and income statements. Compustat and Osiris only contain firms listed on the stock market, so they typically exclude smaller firms. However, they should capture the most R&D intensive firms, as R&D is typically concentrated in publicly listed firms [cf. e.g. Bloom et al., 2013]. The Online Appendix H.3 provides additional details about the accounting databases used in this study.

For the purpose of matching firms across databases, we again use the above mentioned name matching algorithm. We could match roughly 26% of the firms in the alliance data (considering only firms with accounting information available). From our match between the firms' names in the alliance database and the firms' names in the Compustat and Osiris databases, we obtained a firm's sales and R&D expenditures. Individual firms' output levels are computed from deflated sales using 2-SIC digit industry-year specific price deflators from the OECD-STAN database [cf. Gal, 2013]. Furthermore, we use information on R&D expenditures to compute R&D capital stocks using a perpetual inventory method with a 15% depreciation rate (following Bloom et al. [2013]). Considering only firms with non-missing observations on sales, output and R&D expenditures we end up with a sample of $1,186$ firms and a total of 1010 collaborations over the years 1967 to 2006.[10] Basic summary statistics can be found in Table 1.

[10]See the Online Appendix H for a discussion about the representativeness of our data

[*Insert Table 1 here*]

6. Econometric Analysis

6.1. Econometric Specification

In this section, we introduce the econometric equivalent to the equilibrium quantity produced by each firm given in Equation (10). Our empirical counterpart of the marginal cost c_{it} of firm i from Equation (2) at period t has a fixed cost equal to $\bar{c}_{it} = \eta_i^* - \epsilon_{it} - x_{it}\beta$, and thus we get

$$c_{it} = \eta_i^* - \epsilon_{it} - \beta x_{it} - e_{it} - \varphi \sum_{j=1}^{n} a_{ij,t} e_{jt}, \tag{22}$$

where x_{it} is a measure for the productivity of firm i, η_i^* captures the unobserved (to the econometrician) time-invariant characteristics of the firm, and ϵ_{it} captures the remaining unobserved (to the econometrician) characteristics of the firm.

Following Equation (1), the inverse demand function for firm i is given by

$$p_{it} = \bar{\alpha}_m + \bar{\alpha}_t - q_{it} - \rho \sum_{j=1}^{n} b_{ij} q_{jt}, \tag{23}$$

where $b_{ij} = 1$ if i and j are in the same market and zero otherwise. In this equation, $\bar{\alpha}_m$ indicates the market-specific fixed effect and $\bar{\alpha}_t$ captures the time fixed effect due to exogenous demand shifters that affect consumer income, number of consumers, consumer taste and preferences, and expectations over future prices of complements and substitutes and future income.

Denote by $\kappa_t \equiv \bar{\alpha}_t$ and $\eta_i \equiv \bar{\alpha}_m - \eta_i^*$. Observe that κ_t captures the time fixed effect while η_i, which includes both $\bar{\alpha}_m$ and η_i^*, captures the firm fixed effect. Adding subscript t for time and using Equations (22) and (23), the econometric equivalent to the

sample, and Online Appendix J.5 for a discussion about the impact of missing data on our estimation results.

best-response quantity in Equation (10) is given by:

$$q_{it} = \varphi \sum_{j=1}^{n} a_{ij,t} q_{jt} - \rho \sum_{j=1}^{n} b_{ij} q_{jt} + \beta x_{it} + \eta_i + \kappa_t + \epsilon_{it}. \tag{24}$$

Observe that the econometric specification in Equation (24) has a similar specification as the product competition and technology spillover production function estimation in Bloom et al. [2013] where the estimation of φ will give the intensity of the *technology (or knowledge) spillover effect* of R&D, while the estimation of ρ will give the intensity of the *product rivalry effect*. However, as opposed to that paper, we explicitly model the technology spillovers stemming from R&D collaborations using a network approach.

In vector-matrix form, we can write Equation (24) as

$$\mathbf{q}_t = \varphi \mathbf{A}_t \mathbf{q}_t - \rho \mathbf{B} \mathbf{q}_t + \mathbf{x}_t \beta + \boldsymbol{\eta} + \kappa_t \boldsymbol{\iota}_n + \boldsymbol{\epsilon}_t, \tag{25}$$

where $\mathbf{q}_t = (q_{1t}, \cdots, q_{nt})^\top$, $\mathbf{A}_t = [a_{ij,t}]$, $\mathbf{B} = [b_{ij}]$, $\mathbf{x}_t = (x_{1t}, \cdots, x_{nt})^\top$, $\boldsymbol{\eta} = (\eta_1, \cdots, \eta_n)^\top$, $\boldsymbol{\epsilon}_t = (\epsilon_{1t}, \cdots, \epsilon_{nt})^\top$, and $\boldsymbol{\iota}_n$ is an n-dimensional vector of ones.

For the T periods, Equation (25) can be written as

$$\mathbf{q} = \varphi \mathrm{diag}\{\mathbf{A}_t\} \mathbf{q} - \rho (\mathbf{I}_T \otimes \mathbf{B}) \mathbf{q} + \mathbf{x} \beta + \boldsymbol{\iota}_T \otimes \boldsymbol{\eta} + \boldsymbol{\kappa} \otimes \boldsymbol{\iota}_n + \boldsymbol{\epsilon}, \tag{26}$$

where $\mathbf{q} = (\mathbf{q}_1^\top, \cdots, \mathbf{q}_T^\top)^\top$, $\mathbf{x} = (\mathbf{x}_1^\top, \cdots, \mathbf{x}_T^\top)^\top$, $\boldsymbol{\kappa} = (\kappa_1, \cdots, \kappa_T)^\top$, and $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}_1^\top, \cdots, \boldsymbol{\epsilon}_T^\top)^\top$. The vectors $\mathbf{q}$, $\mathbf{x}$ and $\boldsymbol{\epsilon}$ are of dimension $(nT \times 1)$, where T is the number of years available in the data.

In terms of data, our main variables will be measured as follows. Output q_{it} is calculated using sales divided by the year-industry price deflators from the OECD-STAN database. The network data stems from the combined CATI-SDC databases and we set $a_{ij,t} = 1$ if there exists an R&D collaboration between firms i and j in the last s years before time t, where s is the duration of an alliance. The exogenous variable x_{it} is the firm's time-lagged R&D stock at the time $t-1$. Finally, we measure b_{ij} as in the theoretical model so that $b_{ij} = 1$ if firms i and j are the same industry (measured by the industry SIC codes at the 4-digit level) and $b_{ij} = 0$ otherwise.

6.2. Identification Issues

We adopt a structural approach in the sense that we estimate the first-order condition of the firms' profit maximization problem in terms of output and R&D effort, which leads to Equation (24) or (25). The best-response quantity in Equation (25) then corresponds to a higher-order Spatial Auto-Regressive (SAR) model with two spatial lags, $\mathbf{A}_t\mathbf{q}_t$ and $\mathbf{B}\mathbf{q}_t$ [cf. Lee and Liu, 2010].

There are several potential identification problems in the estimation of Equation (24) or (25). We face, actually, four sources of potential bias arising from (i) *correlated or common-shock effects*, (ii) *simultaneity* of q_{it} and q_{jt}, (iii) *endogeneity of the R&D stock*, and (iv) *endogeneity of the R&D alliance matrix*.

6.2.1. Correlated or Common-Shock Effects

Correlated or common-shock effects arise in network models due to the fact that there may be common environmental factors that cause the firms in the same network to behave in a similar manner. They may be confounded with the network effects (i.e. φ and ρ) we are trying to identify. To alleviate this problem, we incorporate both firm and time fixed effects (i.e. η_i and κ_t) to Equation (24).

6.2.2. Simultaneity of Product Outputs

We use instrumental variables when estimating our outcome Equation (24) to deal with the issue of simultaneity between q_{it} and q_{jt}. Indeed, the output of firm i at time t, q_{it}, is a function of the total output of all firms collaborating in R&D with firm i at time t, i.e. $\bar{q}_{a,it} \equiv \sum_{j=1}^{n} a_{ij,t}q_{jt}$, and the total output of all firms that operate in the same market as firm i, i.e. $\bar{q}_{b,it} \equiv \sum_{j=1}^{n} b_{ij}q_{jt}$. Due the feedback effect, q_{jt} also depends on q_{it} and, thus, $\bar{q}_{a,it}$ and $\bar{q}_{b,it}$ are endogenous.

Recall that x_{it} denotes the time-lagged R&D stock of firm i at the time $t-1$. To deal with this issue, we instrument $\bar{q}_{a,it}$ by the time-lagged total R&D stock of all firms with an R&D collaboration with firm i, i.e. $\sum_{j=1}^{n} a_{ij,t} x_{jt}$, and instrument $\bar{q}_{b,it}$ by the time-lagged total R&D stock of all firms that operate in the same industry as firm i, i.e. $\sum_{j=1}^{n} b_{ij} x_{jt}$. The rationale for this IV strategy is that the time-lagged total R&D stock of R&D collaborators and product competitors of firm i *directly* affects the total output of these firms but only *indirectly* affects the output of firm i through the total output of these same firms.

More formally, to estimate Equation (26), first we transform it with the projection matrix $\mathbf{J} = (\mathbf{I}_T - \frac{1}{T}\boldsymbol{\iota}_T\boldsymbol{\iota}_T^\top) \otimes (\mathbf{I} - \frac{1}{n}\boldsymbol{\iota}_n\boldsymbol{\iota}_n^\top)$. The transformed Equation (26) is

$$\mathbf{J}\mathbf{q} = \varphi \mathbf{J}\mathrm{diag}\{\mathbf{A}_t\}\mathbf{q} - \rho\mathbf{J}(\mathbf{I}_T \otimes \mathbf{B})\mathbf{q} + \mathbf{J}\mathbf{x}\beta + \mathbf{J}\boldsymbol{\epsilon}, \tag{27}$$

where the firm and time fixed effects $\boldsymbol{\eta}$ and $\boldsymbol{\kappa}$ have been eliminated by the projection matrix.[11] Let $\mathbf{Q}_1 = \mathbf{J}[\mathrm{diag}\{\mathbf{A}_t\}\mathbf{x}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{x}, \mathbf{x}]$ denote the IV matrix and $\mathbf{Z} = \mathbf{J}[\mathrm{diag}\{\mathbf{A}_t\}\mathbf{q}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{q}, \mathbf{x}]$ denote the matrix of regressors in Equation (27). As there is a single exogenous variable in Equation (27), the model is just-identified. The IV estimator of parameters $(\varphi, -\rho, \beta)^\top$ is given by $(\mathbf{Q}_1^\top\mathbf{Z})^{-1}\mathbf{Q}_1^\top\mathbf{q}$. With the estimated $(\varphi, -\rho, \beta)^\top$, one can recover $\boldsymbol{\eta}$ and $\boldsymbol{\kappa}$ by the least squares dummy variables method.

Obviously, the above IV-based identification strategy is valid only if the time-lagged R&D stock, $x_{i,t-1}$, and the R&D alliance matrix, $\mathbf{A}_t = [a_{ij,t}]$, are exogenous. In Section 6.2.3 we address the potential endogeneity of the time-lagged R&D stock, while the endogeneity of the R&D alliance matrix is discussed in Section 6.2.4.

6.2.3. Endogeneity of the R&D Stock

The R&D stock depends on past R&D efforts, which could be correlated with the error term of Equation (24). However, as the R&D stock is time-lagged and fixed effects are included, the existing literature has argued that the correlation between the (time-lagged) R&D stock and the error term of Equation (24) is likely to be weak. To further alleviate

[11]For unbalanced panels, the firm and time fixed effects can be eliminated by a projection matrix given in Wansbeek and Kapteyn [1989].

the potential endogeneity issue of the time-lagged R&D stock, we use supply side shocks from tax-induced changes to the user cost of R&D to construct IVs as in Bloom et al. [2013]. To be more specific, we use changes in the firm-specific tax price of R&D to construct instrumental variables for R&D expenditures. Let w_{it} denote the time-lagged R&D tax credit firm i received at time $t-1$.[12] We instrument $\bar{q}_{a,it}$ by the time-lagged total R&D tax credits of all firms having R&D collaborations with firm i, i.e. $\sum_{j=1}^{n} a_{ij,t} w_{jt}$, instrument $\bar{q}_{b,it}$ by the time-lagged total R&D tax credits of all firms that operate in the same industry as firm i, i.e. $\sum_{j=1}^{n} b_{ij} w_{jt}$, and instrument the time-lagged R&D stock x_{it} by the time-lagged R&D tax credit w_{it}. The rationale for this IV strategy is that the time-lagged total R&D credits of R&D collaborators and product competitors of firm i *directly* affects the total output of these firms but only *indirectly* affects the output of firm i through the total output of these same firms.

More formally, let $\mathbf{Q}_2 = \mathbf{J}[\text{diag}\{\mathbf{A}_t\}\mathbf{w}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{w}, \mathbf{w}]$, where $\mathbf{w} = (\mathbf{w}_1^\top, \cdots, \mathbf{w}_T^\top)^\top$ and $\mathbf{w}_t = (w_{1t}, \cdots, w_{nt})^\top$, denote the IV matrix, and $\mathbf{Z} = \mathbf{J}[\text{diag}\{\mathbf{A}_t\}\mathbf{q}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{q}, \mathbf{x}]$ denote the matrix of regressors in Equation (27). The IV estimator of parameters $(\varphi, -\rho, \beta)^\top$ is given by $(\mathbf{Q}_2^\top \mathbf{Z})^{-1}\mathbf{Q}_2^\top \mathbf{q}$.

6.2.4. Endogeneity of the R&D Alliance Matrix

The R&D alliance matrix $\mathbf{A}_t = [a_{ij,t}]$ is endogenous if there exists an *unobservable factor* that affects both the outputs, q_{it} and q_{jt}, and the R&D alliance, indicated by $a_{ij,t}$. If the unobservable factor is firm-specific, then it is captured by the firm fixed-effect η_i. If the unobservable factor is time-specific, then it is captured by the time fixed-effect κ_t. Therefore, the fixed effects in the panel data model are helpful for attenuating the potential endogeneity of $\mathbf{A}_t$.

However, it may still be that there are some unobservable firm-specific time-varying factors that affect the formation of R&D collaborations and thus make the R&D alliance matrix $\mathbf{A}_t$ endogenous. To deal with this issue, we run a two-stage IV estimation as in

[12] See Appendix B.3 in the Supplementary Material of Bloom et al. [2013] for details on the specification of w_{it}.

Kelejian and Piras [2014] where, in the first stage, we obtain a predicted R&D alliance matrix based on predetermined dyadic characteristics, and, in the second stage, we employ the IV strategy explained above using IVs constructed with the predicted adjacency matrix from the first stage.

Let us now explain how to obtain a predicted R&D alliance matrix in the first stage. We estimate a logistic regression model with the corresponding log-odds ratio as a function of predetermined dyadic characteristics:

$$\log\left(\frac{\mathbb{P}\left(a_{ij,t}=1 \mid (\mathbf{A}_\tau)_{\tau=1}^{t-s-1}, f_{ij,t-s-1}, city_{ij}, market_{ij}\right)}{1-\mathbb{P}\left(a_{ij,t}=1 \mid (\mathbf{A}_\tau)_{\tau=1}^{t-s-1}, f_{ij,t-s-1}, city_{ij}, market_{ij}\right)}\right)$$
$$= \gamma_0 + \gamma_1 \max_{\tau=1,\ldots,t-s-1} a_{ij,\tau} + \gamma_2 \max_{\substack{\tau=1,\ldots,t-s-1 \\ k=1,\ldots,n}} a_{ik,\tau}a_{kj,\tau} + \gamma_3 f_{ij,t-s-1} + \gamma_4 f_{ij,t-s-1}^2 + \gamma_5 city_{ij} + \gamma_6 market_{ij}, \tag{28}$$

In this model, $\max_{\tau=1,\ldots,t-s-1} a_{ij,\tau}$ is a dummy variable, which is equal to 1 if firms i and j had an R&D collaboration before time $t-s$ (s is the duration of an alliance) and 0 otherwise; $\max_{\tau=1,\ldots,t-s-1;k=1,\ldots,n} a_{ik,\tau}a_{kj,\tau}$ is a dummy variable, which is equal to 1 if firms i and j had a common R&D collaborator before time $t-s$ and 0 otherwise; $f_{ij,t-s-1}$ is the time-lagged technological proximities between firms i and j, measured here by either the Jaffe or the Mahalanobis patent similarity indices at time $t-s-1$;[13] $city_{ij}$ is a dummy

[13] We matched the firms in our alliance data with the owners of patents recorded in the Worldwide Patent Statistical Database (PATSTAT). This allowed us to obtain the number of patents and the patent portfolio held for about 36% of the firms in the alliance data. From the firms' patents, we then computed their technological proximity following Jaffe [1986] as $f_{ij}^{\mathrm{J}} = \frac{\mathbf{P}_i^\top \mathbf{P}_j}{\sqrt{\mathbf{P}_i^\top \mathbf{P}_i}\sqrt{\mathbf{P}_j^\top \mathbf{P}_j}}$, where $\mathbf{P}_i$ represents the patent portfolio of firm i and is a vector whose k-th component P_{ik} counts the number of patents firm i has in technology category k divided by the total number of technologies attributed to the firm. As an alternative measure for technological similarity we also use the Mahalanobis proximity index f_{ij}^{M} introduced in Bloom et al. [2013]. The Online Appendix H.5 provides further details about the match of firms to their patent portfolios and the construction of the

variable, which is equal to 1 if firms i and j are located in the same city and 0 otherwise; and $market_{ij}$ is a dummy variable, which is equal to 1 if firms i and j are in the same market and 0 otherwise.

The rationale for this IV solution is as follows. Take, for example, the dummy variable, which is equal to 1 if firms i and j had a common R&D collaborator before time $t-s$, and 0 otherwise. This means that, if firms i and j had a common collaborator in the past (i.e. before time $t-s$), then they are more likely to have an R&D collaboration in period t, i.e. $a_{ij,t}=1$, but, conditional on the firm and time fixed effects, having a common collaborator in the past should not *directly* affect the outputs of firms i and j in period t (i.e. the exclusion restriction is satisfied). A similar argument can be made for the other variables in Equation (28). As a result, using IVs based on the predicted adjacency matrix $\widehat{\mathbf{A}}_t$ should alleviate the concern of invalid IVs due to the endogeneity of the adjacency matrix $\mathbf{A}_t$.

Formally, let $\mathbf{Q}_3 = \mathbf{J}[\mathrm{diag}\{\widehat{\mathbf{A}}_t\}\mathbf{x}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{x}, \mathbf{x}]$ denote the IV matrix based on the predicted R&D alliance matrix and $\mathbf{Z} = [\mathrm{diag}\{\mathbf{A}_t\}\mathbf{q}, (\mathbf{I}_T \otimes \mathbf{B})\mathbf{q}, \mathbf{x}]$ denote the matrix of regressors in Equation (27). Then, the estimator of the parameters $(\varphi, -\rho, \beta)^{\top}$ with IVs based on the predicted adjacency matrix is given by $(\mathbf{Q}_2^{\top}\mathbf{Z})^{-1}\mathbf{Q}_3^{\top}\mathbf{q}$.

6.3. Estimation Results

6.3.1. Main results

Table 2 reports the parameter estimates of Equation (25) with time fixed effects (Model A) and with both firm and time fixed effects (Model B). We see that, with both firm and time fixed effects, there is a significant and positive *technology spillover effect*, which indicates that the higher a firm's production level (or R&D effort) is, the more its R&D collaborator produces. That is, there exist *strategic complementarities* between allied firms in production and R&D effort. On the other hand, there is a significant and negative *product rivalry effect*, which indicates that the higher a firm's production level (or R&D

technology proximity measures f_{ij}^k, $k \in \{\mathrm{J}, \mathrm{M}\}$.

effort) is, the less its product competitors in the same market produce. Furthermore, this table also shows that a firm's productivity captured by its own time-lagged R&D stock has a positive and significant impact on its own production level. Finally, the Cragg-Donald Wald F statistics for both models are well above the conventional benchmark for weak IVs [cf. Stock and Yogo, 2005].

[*Insert Table* 2 *here*]

6.3.2. Endogeneity of R&D Stocks and Tax-Credit Instruments

Table 3 reports the parameter estimates of Equation (25) with tax credits as IVs for the time-lagged R&D stock as discussed in Section 6.2.3. Similarly to the benchmark results reported in Section 6.3.1, with both firm and time fixed effects, the estimated parameters in Model D are statistically significant with the expected signs, i.e., the *technology (or knowledge) spillover effect* is positive while the *product rivalry effect* is negative.

[*Insert Table* 3 *here*]

6.3.3. Endogeneity of the R&D Alliance Matrix

We also consider IVs based on the predicted R&D alliance matrix, i.e. $\widehat{\mathbf{A}}_t\mathbf{x}_t$, as discussed in Section 6.2.3. First, we obtain the predicted alliance-formation probability $\hat{a}_{ij,t}$ from the logistic regression given by Equation (28). The logistic regression result, using either the Jaffe or Mahalanobis patent similarity measures, is reported in Table 4. The estimated coefficients are all statistically significant with expected signs. Interestingly, having a past collaboration or a past common collaborator, being established in the same city, or operating in the same industry/market increases the probability that two firms have an R&D collaboration in the current period. Furthermore, being close in technology (measured by either the Jaffe or Mahalanobis patent similarity measure) in the past also increases the chance of having an R&D collaboration in the current period.

Next, we estimate Equation (25) with IVs based on the predicted alliance matrix.

The estimates are reported in Table 5. We find that the estimates of both the technology spillovers and the product rivalry effect are still significant with the expected signs. Compared to Table 2, the estimate of the technology spillovers (i.e. the estimation of φ) has, however, a larger value and a larger standard error. Finally, the reported Cragg-Donald Wald F statistics suggest the IVs based on the predicted alliance matrix are informative.

[*Insert Tables 4 and 5 here*]

6.3.4. Robustness Analysis

In the Online Appendix J, we perform some additional robustness checks. First, in Online Appendix J.1, we estimate our model for alliance durations ranging from 3 to 7 years. Second, in Online Appendix J.2, we consider a model where the spillover and competition coefficients are *not* identical across markets. We perform a robustness check using two major divisions in our data, namely the manufacturing and services sectors that cover, respectively, 76.8% and 19.3% firms in our sample. Third, in Online Appendix J.3, we conduct a robustness analysis by directly controlling for potential input-supplier effects. Fourth, in Online Appendix J.4, we consider three alternative specifications of the competition matrix. Finally, in Online Appendix J.5, we discuss the issue of possible biases due to sampled network data. We find that the estimates are robust to all these extensions.

6.4. Direct and Indirect Technology Spillovers

In this section, we extend our empirical model of Equation (24) by allowing for both, direct (between firms with an R&D alliance) and indirect (between firms without an R&D alliance) technology spillovers. The generalized model is given by[14]

$$q_{it} = \varphi \sum_{j=1}^{n} a_{ij,t} q_{jt} + \chi \sum_{j=1}^{n} f_{ij,t} q_{jt} - \rho \sum_{j=1}^{n} b_{ij} q_{jt} + \beta x_{it} + \eta_i + \kappa_t + \epsilon_{it}, \tag{29}$$

[14]The theoretical foundation of Equation (29) can be found in the Online Appendix F.

where $f_{ij,t}$ are weights characterizing alternative channels for technology spillovers (measured by the technological proximity between firms using either the Jaffe or the Mahalanobis patent similarity measures; see Bloom et al. [2013] and Online Appendix H.5) other than R&D collaborations, and the coefficients φ and χ capture the direct and the indirect technology spillover effects, respectively. In vector-matrix form, we then have

$$\mathbf{q}_t = \varphi \mathbf{A}_t \mathbf{q}_t + \chi \mathbf{F}_t \mathbf{q}_t - \rho \mathbf{B} \mathbf{q}_t + \mathbf{x}_t \beta + \boldsymbol{\eta} + \kappa_t \boldsymbol{\iota}_n + \boldsymbol{\epsilon}_t. \tag{30}$$

The results of a fixed-effect panel regression of Equation (30) are shown in Table 6. Both technology spillover coefficients, φ and χ, are positive, while only the direct spillover effect is significant. This suggests R&D network alliances are the main channel for technology spillovers.

[*Insert Table 6 here*]

7. Empirical Implications for the R&D Subsidy Policy

With our estimates from the previous sections – using Model B in Table 2 as our baseline specification – we are now able to empirically determine the optimal subsidy policy, both for the homogenous case, where all firms receive the same subsidy per unit of R&D (see Proposition 2), and for the targeted case, where the subsidy per unit of R&D may vary across firms (see Proposition 3).[15]

As our empirical analysis focuses on U.S. firms, the central planner that would implement such an R&D subsidy policy could be the U.S. government or a U.S. governmental agency. In the U.S., R&D policies have been widely used to foster the firms' R&D activities. In particular, as of 2006, 32 states in the U.S. provided a tax credit on general, company funded R&D [cf. Wilson, 2009]. Moreover, another prominent example in

[15]Additional details about the numerical implementation of the optimal subsidies program can be found in Online Appendix I.

the U.S. is the Advanced Technology Program (ATP), which was administered by the National Institute of Standards and Technology (NIST) [cf. Feldman and Kelley, 2003].

Observe that we provide a *network-contingent* subsidy program, that is, each time an R&D subsidy policy is implemented, it takes into account the prevalent network structure. In other words, we determine how, for any observed network structure, the R&D policy should be specified (short-run perspective). The rationale for this approach is that, in an uncertain and highly dynamic environment such as the R&D intensive industries that we consider, an *optimal contingent policy* is typically preferable over a *fixed policy* [see, e.g. Buiter, 1981]. In the following we will then calculate the optimal subsidy for each firm in every year that the network is observed.

[*Insert Figure 2 here*]

In Figure 1, in the top panel, we calculate the optimal homogenous subsidy times R&D effort over time, using the subsidies in the year 1990 as the base level (top left panel), and the percentage increase in welfare due to the homogenous subsidy over time (top right panel). The total subsidized R&D effort more than doubled over the time between 1990 and 2005. In terms of welfare, the highest increase (around 3.5 %) is obtained in the year 2001, while the increase in welfare in 1990 is smaller (below 2.5 %). The bottom panel of Figure 1 performs the same exercise for the targeted subsidy policy. The targeted subsidy program turns out to have a much higher impact on total welfare, as it can improve welfare by up to 80 %, while the homogeneous subsidies can improve total welfare only by up to 3.5 %. Moreover, the optimal subsidy levels show a strong variation over time.

We can compare the optimal subsidy level predicted from our model with the R&D tax subsidies actually implemented in the United States and selected other countries between 1979 to 1997 [see Bloom et al., 2002]. While these time series typically show a steady increase of R&D subsidies over time, they do not seem to incorporate the cyclicality that we obtain for the optimal subsidy levels. Our analysis thus suggests that policy makers should adjust R&D subsidies to these cycles.

We next proceed by providing a ranking of firms in terms of targeted subsidies. Such a ranking can guide a planner that wants to maximize total welfare by introducing an R&D subsidy program and identify which firms should receive the highest subsidies. The ranking of the first 25 firms by their optimal subsidy levels in 1990 can be found in Table 7 while the one for 2005 is shown in Table 8.[16] We see that the ranking of firms in terms of subsidies does not correspond to other rankings in terms of network centrality, patent stocks or market share.

There is also volatility in the ranking since many firms that are ranked in the top 25 in 1990 are no longer there in 2005 (for example *TRW Inc.*, *Alcoa Inc.*, *Schlumberger Ltd. Inc.*, etc.). Figure 2 shows the change in the ranking of the 25 highest subsidized firms (Table 7) from 1990 to 2005.

A comparison of market shares, R&D stocks, the number of patents, the degree (i.e. the number of R&D collaborations), the homogeneous subsidy and the targeted subsidy shows a high correlation between the R&D stock and the number of patents, with a (Spearman) correlation coefficient of 0.65 for the year 2005. A high correlation can also be found for the homogeneous subsidy and the targeted subsidy, with a correlation coefficient of 0.75 for the year 2005. We also find that highly subsidized firms tend to have a larger R&D stock, and also a larger number of patents, degree and market share. However, these measures can only partially explain the subsidies ranking of the firms, as the market share is more related to the product market rivalry effect, while the R&D and patent stocks are more related to the technology spillover effect, and both enter into the computation of the optimal subsidy program.

Observe that our subsidy rankings typically favor larger firms as they tend to be better connected in the R&D network than small firms. This adds to the discussion of whether large or small firms are contributing more to the innovativeness of an economy,

[16]The network statistics shown in these tables correspond to the full CATI-SDC network dataset, prior to dropping firms with missing accounting information. See Online Appendix H.1 for more details about the data sources and construction of the R&D alliances network.

by adding another dimension along which larger firms can have an advantage over small ones, namely by creating R&D spillover effects that contribute to the overall productivity of the economy. While studies such as Spencer and Brander [1983] and Acemoglu et al. [2012] find that R&D should often be taxed rather than subsidized, we find that R&D subsidies can have a significantly positive effect on welfare. The reason why our results differ from that of these studies is that we take into account the consumer surplus when deriving the optimal R&D subsidy. Moreover, in contrast to Acemoglu et al. [2012], we do not focus on entry and exit but incorporate the network of R&D collaborating firms. This allows us to take into account the R&D spillover effects of incumbent firms, which are typically ignored in studies of the innovative activity of incumbent firms versus entrants.

[*Insert Tables* 7 *and* 8 *here*]

8. Discussion

In this section we discuss some assumptions of our model and their implications on the empirical and policy analyses.

Inertia of R&D networks One of the underlying assumptions of our model is that the R&D network exhibits inertia. That is, compared to making adjustments to production and R&D expenditures, it is relatively costly – both in terms of money and time – to form new alliances in the R&D network. Therefore, we consider a short-run policy analysis, where we treat the R&D network as given and design the optimal subsidy program by taking into account the equilibrium production and R&D investment decisions of the firms. In the long run, the R&D network might itself also respond to the subsidy program, and thus, the design of a long-run subsidy program should take the evolution of the R&D network into account. However, such a dynamic forward looking network formation game would be very hard to solve. For this reason, we focus on a short-run policy analysis in this paper, leaving the long-run policy analysis for future work.

Independent markets In our basic model, we consider independent markets, i.e., firms only compete against firms in the same product market, but not against firms from different product markets. This assumption can be relaxed, however, in our theoretical framework. In Proposition 1 we characterize the Nash equilibrium with a single product market (i.e., $M = 1$), where all firms compete against each other. Furthermore, by allowing the elements of the competition matrix $\mathbf{B}$ to take arbitrary weights instead of the binary values 0 or 1, the competition matrix can be flexibly specified to represent more general market structures.

Based on these ideas, we conduct a robustness analysis for our empirical results with alternative specifications of the competition matrix. First, in Section J.2 of the Online Appendix, we re-estimate Equation (26) using two major sectors in our data, namely the manufacturing and services sectors, that, respectively, cover 76.8% and 19.3% firms in our sample. The estimated spillover and competition parameters of these two sectors are largely the same as those in our benchmark specification.

Next, in Section J.4 of the Online Appendix, we consider a richer specification of the $\mathbf{B}$ matrix. This extension follows Bloom et al. [2013] by considering three alternative specifications for the competition matrix based on the primary and secondary industry classification codes that can be found in (i) the Compustat Segments database, (ii) the Orbis database [cf. Bloom et al., 2013], or (iii) the Hoberg-Phillips product similarity database [cf. Hoberg and Phillips , 2016]. These alternative competition matrices capture (in a reduced form) the product portfolio of a firm by taking into account the different industries a firm is operating in. We find that irrespective of what type of competition matrix is being used, the estimated technology spillover effect is positively significant, with the magnitude similar to that obtained in the benchmark model. Moreover, the product rivalry effect with alternative specifications of the competition matrix is also statistically significant with the expected sign.

No input-output linkages Our theoretical model considers horizontally related firms, while it does not incorporate the possible vertical relationships of firms through input-output linkages. To test for potential R&D spillovers between vertically related firms, we conduct a robustness analysis by directly controlling for potential input-supplier effects. We obtain information about firms' buyer-supplier relationships from two data sources. The first is the Compustat Segments database [cf. e.g. Atalay et al., 2011]. Compustat Segments provides business details, product information and customer data for over 70% of the companies in the Compustat North American database, with firms' coverage starting in the year 1976. We also use as a second datasource the Capital IQ Business Relationships database [Mizuno et al., 2014]. The Capital IQ data includes any customers/suppliers that are mentioned in the firms' annual reports, news, websites surveys etc, with firms coverage starting in the year 1990. We then merged these two datasources to obtain a more complete picture of the potential buyer-supplier linkages between the firms in our R&D network. Aggregated over all years we obtained a total of $2,573$ buyer-supplier relationships for the firms matched with our R&D network dataset. Using these data on firms' buyer-supplier relationships, we find that, after controlling for the input-supplier effect, the spillover and competition effects remain statistically significant with the expected signs.

No market entry and exit As we focus on a short-run policy analysis in this paper, we consider only incumbent firms and abstract from the complication of market entry and exit. This allows us to study the R&D spillover effects using a network approach, which are typically ignored in studies of innovative activities of incumbent firms versus entrants as for example Acemoglu et al. [2012]. Therefore, we see our analysis as complementary to that of Acemoglu et al. [2012], and we show that R&D subsidies can trigger considerable welfare gains when technology spillovers through R&D alliances are taken into account.

No foreign firms Another possible extension of the current model is to partition the firms into domestic firms and foreign firms, and consider a subsidy program that only subsidizes domestic firms. This extension would be possible under our current framework as our targeted subsidy program is very flexible. In particular, it is allowed to assign zero subsidies to certain firms (e.g. foreign firms). However, we do not pursue this extension in this paper as in the data we only consider U.S. firms.

9. Conclusion

In this paper, we have developed a model where firms benefit form R&D collaborations (networks) to lower their production costs while at the same time competing on the product market. We have highlighted the positive role of the network in terms of technology spillovers and the negative role of product rivalry in terms of market competition. We have also determined the importance of targeted subsidies on the total welfare of the economy.

Using a panel of R&D alliance networks and annual reports, we have then tested our theoretical results and first showed that both, the technology spillover effect and the market competition effect have the expected signs and are significant. We have also identified the firms in our data that should be subsidized the most to maximize welfare in the economy. Finally, we have drawn some policy conclusions about optimal R&D subsidies from the results obtained over different sectors, as well as their temporal variation.

We believe that the methodology developed in this paper offers a fruitful way of analyzing the existence of R&D spillovers and their policy implications in terms of firms' subsidies across and within different industries. We also believe that putting forward the role of networks in terms of R&D collaborations is important to understanding the different aspects of these markets.

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Table 1: Summary statistics computed across the years 1967 to 2006.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	Compustat Mean
Sales [10^6]	21,067	2,101.56	7,733.29	9.98×10^{-8}	168,055.80	1,085.05
Empl.	19,709	16,694.82	51,299.36	1	876,800.00	4,322.08
Capital [10^6]	20,873	1,629.29	7,388.32	3.82×10^{-8}	170,437.40	663.44
R&D Exp. [10^6]	18,629	70.75	287.42	5.56×10^{-4}	6,621.19	14.71
R&D Exp. / Empl.	17,203	20,207.79	55,887.27	3.37	2,568,507.00	4,060.12
R&D Stock [10^6]	17,584	406.87	1,520.97	5.58×10^{-3}	22,292.97	33.13
Num. Patents	12,177	2,588.31	7,814.59	1	76,644.00	14.39

Notes: Values for sales, capital and R&D expenses are in U.S. dollars with 1983 as the base year. Compustat means are computed across all firms in the Compustat U.S. fundamentals annual database over all non-missing observations over the years 1967 to 2006.

Table 2: Parameter estimates from a panel regression of Equation (25).

	Model A		Model B	
φ	-0.0118	(0.0075)	0.0106**	(0.0051)
ρ	0.0114***	(0.0015)	0.0189***	(0.0028)
β	0.0053***	(0.0002)	0.0027***	(0.0002)
# firms	1186		1186	
# observations	16924		16924	
Cragg-Donald Wald F stat.	6454.185		7078.856	
firm fixed effects	no		yes	
time fixed effects	yes		yes	

*** Statistically significant at 1% level.

** Statistically significant at 5% level.

* Statistically significant at 10% level.

Table 3: Parameter estimates from a panel regression of Equation (25) with IVs based on time-lagged tax credits.

	Model C		Model D	
φ	-0.0133	(0.0114)	0.0128*	(0.0069)
ρ	0.0182***	(0.0018)	0.0156**	(0.0076)
β	0.0054***	(0.0004)	0.0023***	(0.0006)
# firms	1186		1186	
# observations	16924		16924	
Cragg-Donald Wald F stat.	138.311		78.791	
firm fixed effects	no		yes	
time fixed effects	yes		yes	

*** Statistically significant at 1% level.

** Statistically significant at 5% level.

* Statistically significant at 10% level.

Table 4: Link formation regression results. The dependent variable $a_{ij,t}$ indicates if an R&D alliance exists between firms i and j at time t.

technological similarity	Jaffe	Mahalanobis
Past collaboration	0.5981***	0.5920***
	(0.0150)	(0.0149)
Past common collaborator	0.1162***	0.1164***
	(0.0238)	(0.0236)
$f_{ij,t-s-1}$	13.6977***	6.0864***
	(0.6884)	(0.3323)
$f^2_{ij,t-s-1}$	-20.4083***	-3.9194***
	(1.7408)	(0.4632)
$city_{ij}$	1.1283***	1.1401***
	(0.1017)	(0.1017)
$market_{ij}$	0.8451***	0.8561***
	(0.0424)	(0.0422)
# observations	3,964,120	3,964,120
McFadden's R^2	0.0812	0.0813

*** Statistically significant at 1% level.

** Statistically significant at 5% level.

* Statistically significant at 10% level.

Table 5: Parameter estimates from a panel regression of Equation (25) with endogenous R&D alliance matrix.

technological similarity	Jaffe		Mahalanobis	
φ	0.0582*	(0.0343)	0.0593*	(0.0341)
ρ	0.0197***	(0.0031)	0.0197***	(0.0031)
β	0.0024***	(0.0002)	0.0024***	(0.0002)
# firms	1186		1186	
# observations	16924		16924	
Cragg-Donald Wald F stat.	48.029		49.960	
firm fixed effects	yes		yes	
time fixed effects	yes		yes	

*** Statistically significant at 1% level.

** Statistically significant at 5% level.

* Statistically significant at 10% level.

Table 6: Parameter estimates from a panel regression of Equation (30)

technological similarity	Jaffe		Mahalanobis	
φ	0.0102**	(0.0049)	0.0102**	(0.0049)
χ	0.0063	(0.0052)	0.0043	(0.0030)
ρ	0.0189***	(0.0028)	0.0192**	(0.0028)
β	0.0027***	(0.0002)	0.0027***	(0.0002)
# firms	1190		1190	
# observations	17105		17105	
Cragg-Donald Wald F stat.	4791.308		4303.563	
firm fixed effects	yes		yes	
time fixed effects	yes		yes	

*** Statistically significant at 1% level.

** Statistically significant at 5% level.

* Statistically significant at 10% level.

Table 7: Subsidies ranking for the year 1990 for the first 25 firms.

Firm	Share [%][a]	num pat.	$\mathbf{d}$	$\mathbf{v}_{\mathrm{PF}}$	Betweenness[b]	Closeness[c]	$\mathbf{q}$ [%][d]	hom. sub. [%][e]	tar. sub. [%][f]	SIC[g]	Rank
General Motors Corp.	9.2732	76644	88	0.1009	0.0007	0.0493	6.9866	0.0272	0.3027	3711	1
Exxon Corp.	7.7132	21954	22	0.0221	0.0000	0.0365	5.4062	0.0231	0.1731	2911	2
Ford Motor Co.	7.3456	20378	6	0.0003	0.0000	0.0153	3.7301	0.0184	0.0757	3711	3
AT&T Corp.	9.5360	5692	8	0.0024	0.0000	0.0202	3.2272	0.0156	0.0565	4813	4
Chevron	2.8221	12789	23	0.0226	0.0001	0.0369	2.5224	0.0098	0.0418	2911	5
Texaco	2.9896	9134	22	0.0214	0.0000	0.0365	2.4965	0.0095	0.0415	2911	6
Lockheed	42.3696	2	51	0.0891	0.0002	0.0443	1.5639	0.0035	0.0196	3760	7
Mobil Corp.	4.2265	3	0	0.0000	0.0000	0.0000	1.9460	0.0111	0.0191	2911	8
TRW Inc.	5.3686	9438	43	0.0583	0.0002	0.0415	1.4509	0.0027	0.0176	3714	9
Altria Group	43.6382	0	0	0.0000	0.0000	0.0000	1.4665	0.0073	0.0117	2111	10
Alcoa Inc.	11.4121	4546	36	0.0287	0.0002	0.0372	1.2136	0.0032	0.0114	3350	11
Shell Oil Co.	14.6777	9504	0	0.0000	0.0000	0.0000	1.4244	0.0073	0.0109	1311	12
Chrysler Corp.	2.2414	3712	6	0.0017	0.0000	0.0218	1.3935	0.0075	0.0109	3711	13
Schlumberger Ltd. Inc.	25.9218	9	18	0.0437	0.0000	0.0370	1.1208	0.0029	0.0099	1389	14
Hewlett-Packard Co.	7.1106	6606	64	0.1128	0.0002	0.0417	1.1958	0.0047	0.0093	3570	15
Intel Corp.	9.3900	1132	67	0.1260	0.0003	0.0468	1.0152	0.0018	0.0089	3674	16
Hoechst Celanese Corp.	5.6401	516	38	0.0368	0.0002	0.0406	1.0047	0.0021	0.0085	2820	17
Motorola	14.1649	21454	70	0.1186	0.0004	0.0442	1.0274	0.0028	0.0080	3663	18
PPG Industries Inc.	13.3221	24904	20	0.0230	0.0000	0.0366	0.9588	0.0021	0.0077	2851	19
Himont Inc.	0.0000	59	28	0.0173	0.0001	0.0359	0.8827	0.0014	0.0072	2821	20
GTE Corp.	3.1301	4	0	0.0000	0.0000	0.0000	1.1696	0.0067	0.0070	4813	21
National Semiconductor Corp.	4.0752	1642	43	0.0943	0.0001	0.0440	0.8654	0.0012	0.0068	3674	22
Marathon Oil Corp.	7.9828	202	0	0.0000	0.0000	0.0000	1.1306	0.0060	0.0068	1311	23
Bellsouth Corp.	2.4438	3	14	0.0194	0.0000	0.0329	1.0926	0.0060	0.0064	4813	24
Nynex	2.3143	26	24	0.0272	0.0001	0.0340	0.9469	0.0049	0.0052	4813	25

[a] Market share in the primary 4-digit SIC sector in which the firm is operating.

[b] The normalized betweenness centrality is the fraction of all shortest paths in the network that contain a given node, divided by $(n-1)(n-2)$, the maximum number of such paths.

[c] The closeness centrality of node i is computed as $\frac{2}{n-1}\sum_{j=1}^{n} 2^{-\ell_{ij}(G)}$, where $\ell_{ij}(G)$ is the length of the shortest path between i and j in the network G and the factor $\frac{2}{n-1}$ is the maximal centrality attained for the center of a star network.

[d] The relative output of a firm i follows from Proposition 1.

[e] The homogeneous subsidy is computed as $e_i^* s^*$, relative to the total homogeneous subsidies $\sum_{j=1}^{n} e_j^* s^*$ (Proposition 2).

[f] The targeted subsidy for each firm i is computed as $e_i^* s_i^*$, relative to the total targeted subsidies $\sum_{j=1}^{n} e_j^* s_j^*$ (see Proposition 3).

[g] The primary 4-digit SIC code according to Compustat U.S. fundamentals database.

Table 8: Subsidies ranking for the year 2005 for the first 25 firms.

Firm	Share [%][a]	num pat.	$\mathbf{d}$	$\mathbf{v}_{\mathrm{PF}}$	Betweenness[b]	Closeness[c]	$\mathbf{q}$ [%][d]	hom. sub.[%][e]	tar. sub. [%][f]	SIC[g]	Rank
General Motors Corp.	3.9590	90652	19	0.0067	0.0002	0.0193	4.1128	0.0174	0.2186	3711	1
Ford Motor Co.	3.6818	27452	7	0.0015	0.0000	0.0139	3.4842	0.0153	0.1531	3711	2
Exxon Corp.	4.0259	53215	6	0.0007	0.0001	0.0167	2.9690	0.0132	0.1108	2911	3
Microsoft Corp.	10.9732	10639	62	0.1814	0.0020	0.0386	1.6959	0.0057	0.0421	7372	4
Pfizer Inc.	3.6714	74253	65	0.0298	0.0034	0.0395	1.6796	0.0069	0.0351	2834	5
AT&T Corp.	0.0000	16284	0	0.0000	0.0000	0.0000	1.5740	0.0073	0.0311	4813	6
Motorola	6.6605	70583	66	0.1598	0.0017	0.0356	1.3960	0.0053	0.0282	3663	7
Intel Corp.	5.0169	28513	72	0.2410	0.0011	0.0359	1.3323	0.0050	0.0249	3674	8
Chevron	2.2683	15049	10	0.0017	0.0001	0.0153	1.3295	0.0058	0.0243	2911	9
Hewlett-Packard Co.	14.3777	38597	7	0.0288	0.0000	0.0233	1.1999	0.0055	0.0183	3570	10
Altria Group	20.4890	5	2	0.0000	0.0000	0.0041	1.1753	0.0054	0.0178	2111	11
Johnson & Johnson Inc.	3.6095	31931	40	0.0130	0.0015	0.0346	1.1995	0.0051	0.0173	2834	12
Texaco	0.0000	10729	0	0.0000	0.0000	0.0000	1.0271	0.0055	0.0124	2911	13
Shell Oil Co.	0.0000	12436	0	0.0000	0.0000	0.0000	0.9294	0.0045	0.0108	1311	14
Chrysler Corp.	0.0000	5112	0	0.0000	0.0000	0.0000	0.9352	0.0052	0.0101	3711	15
Bristol-Myers Squibb Co.	1.3746	16	35	0.0052	0.0009	0.0326	0.8022	0.0034	0.0077	2834	16
Merck & Co. Inc.	1.5754	52036	36	0.0023	0.0007	0.0279	0.8252	0.0038	0.0077	2834	17
Marathon Oil Corp.	5.5960	229	0	0.0000	0.0000	0.0000	0.7817	0.0039	0.0076	1311	18
GTE Corp.	0.0000	5	0	0.0000	0.0000	0.0000	0.7751	0.0041	0.0073	4813	19
Pepsico	36.6491	991	0	0.0000	0.0000	0.0000	0.7154	0.0035	0.0066	2080	20
Bellsouth Corp.	0.9081	2129	0	0.0000	0.0000	0.0000	0.7233	0.0039	0.0063	4813	21
Johnson Controls Inc.	22.0636	304	11	0.0027	0.0001	0.0159	0.6084	0.0021	0.0063	2531	22
Dell	18.9098	80	2	0.0190	0.0000	0.0216	0.6586	0.0028	0.0061	3571	23
Eastman Kodak Co	5.5952	109714	17	0.0442	0.0001	0.0262	0.6171	0.0023	0.0060	3861	24
Lockheed	48.9385	9817	44	0.0434	0.0003	0.0223	0.6000	0.0028	0.0049	3760	25

Superscripts: a, b, c, d, e, f, g: same as in Table 7.

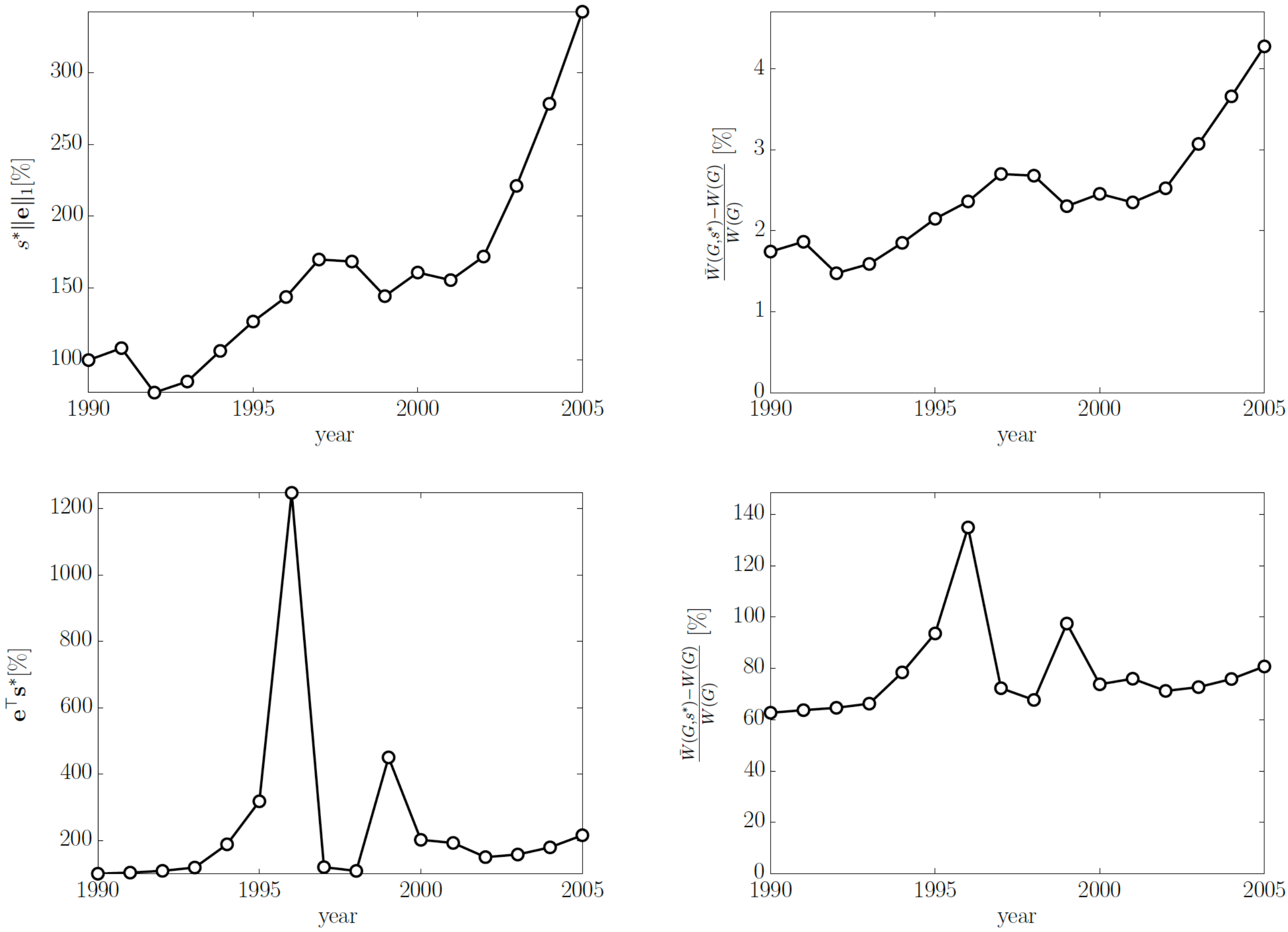

Figure 1: (Top left panel) The total optimal subsidy payments, $s^*\|\mathbf{e}\|_1$, in the homogeneous case over time, using the subsidies in the year 1990 as the base level. (Top right panel) The percentage increase in welfare due to the homogeneous subsidy, s^*, over time. (Bottom left panel) The total subsidy payments, $\mathbf{e}^\top\mathbf{s}^*$, when the subsidies are targeted towards specific firms, using the subsidies in the year 1990 as the base level. (Bottom right panel) The percentage increase in welfare due to the targeted subsidies, $\mathbf{s}^*$, over time.

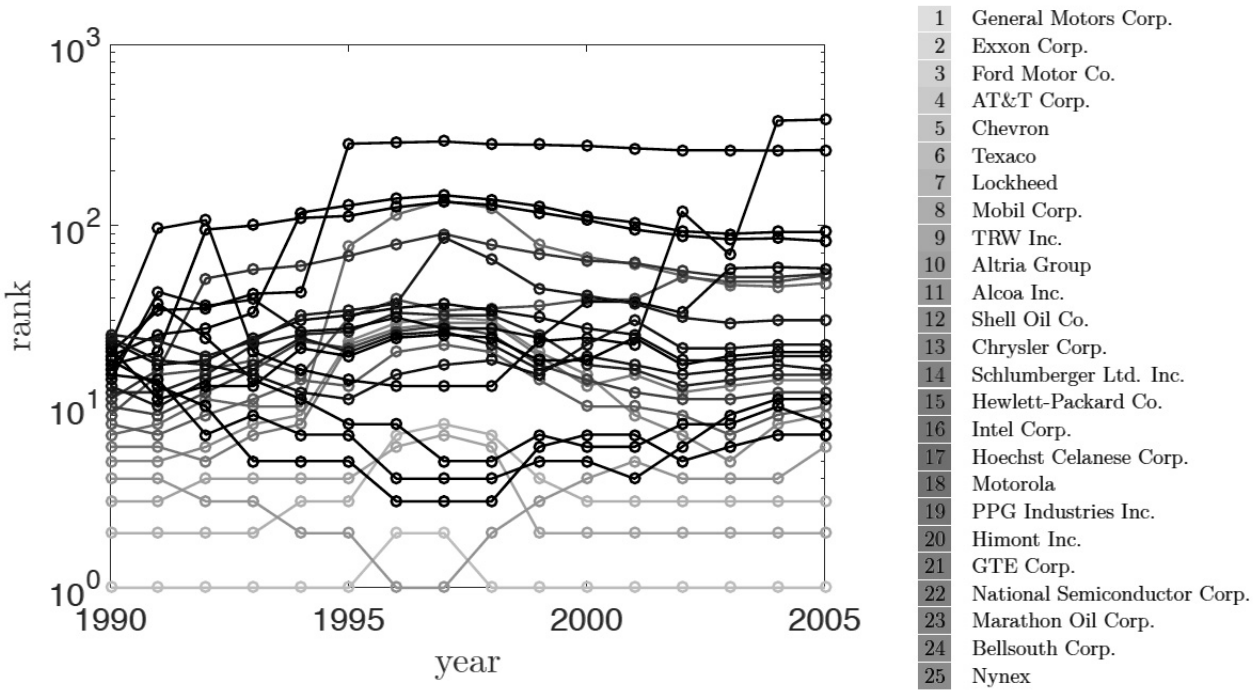

Figure 2: Change in the ranking of the 25 highest subsidized firms (Table 7) from 1990 to 2005.