# Common Ownership and the Market for Technology

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**Abstract**

Using information on U.S. patent reassignments, this paper establishes economically and statistically significant effects of common institutional ownership on the reallocation of technological knowledge between publicly traded companies. The effect is strongest for technologies associated with recent innovations. Higher common ownership with providers leads to more innovations and higher market capitalization growth by adopters. A new identification strategy based on pure-indexer ownership establishes causality. The observed effects are consistent with a matching model in which common owners mitigate moral hazard linked to know-how transmission, increasing transfer quality. The results shed light on the impact of common ownership on managerial decision-making.

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Corporate innovations drive economic growth (Schumpeter, 1911; Aghion and Howitt, 1992) and strongly determine firms' long-term profitability (Arrow, 1962). Beyond innovators, new technologies can generate benefits for other firms and the economy overall. These benefits spread through different channels, including both unintended technology spillovers (Griliches, 1979; Romer, 1983, 1986) and intentionally established markets for ideas (Akcigit, Celik and Greenwood, 2016; Serrano, 2018). Current research shows that the market for technology plays an important role in the diffusion of innovative knowledge, for innovators to profit from their inventions, and as a source of acquiring valuable inputs for adopters (Arqué-Castells and Spulber, 2022).

Despite the potential benefits of technology transfer, its efficient execution may face challenges due to various information and agency frictions, which can cause significant welfare losses and

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undermine the gains from technology adoption.[1] Institutional investors, who often hold diversified portfolios that include both potential providers and adopters of technologies, could help overcome these frictions by encouraging higher-quality transfers or improving information exchange between firms. However, the relationship between technology reallocation and financial markets remains understudied.

In this paper, I seek to explore whether the presence of common institutional owners of publicly traded companies can ease information and agency frictions in the market for technology. Specifically, I consider whether managers of technology providers that share common institutional shareholders with a potential innovation adopter have more incentives to reveal valuable information and thereby increase the benefits of the technology transfer for the acquirer.

By analyzing patent reassignments data, which reflect transfers of intellectual property rights, collected from the United States Patent and Trademark Office (USPTO), I identify two key factors that affect technology reallocation and the advantages of technology adoption: institutional ownership linkages between firms and the monitoring effort of these shared investors. Common ownership between a technology provider and a potential adopter increases the probability that the latter becomes the assignee of the patents. This effect on adopter selection is statistically and economically significant. It is quantitatively stronger for measures of common ownership that account for investors' monitoring efforts with regard to providers' management. Results are robust to controlling for a range of firm, dyad, and adopter-technology characteristics, as well as different approaches for matching counterfactual traders to observed provider-adopter dyadic observations.

To further address potential endogeneity issues, this paper leverages the variation of ownership of publicly traded companies by a subset of passive funds. Unlike other funds that may not replicate an index portfolio accurately, the funds in this subset closely track their benchmark stock market index, holding the underlying assets in similar proportions. Specifically, I focus on the holdings of pure indexer mutual funds that invest in potential adopters and track those indexes to which the technology provider belongs. This creates exogenous variation in common ownership, used to construct an instrumental variable. By employing this identification strategy, I establish a causal link between common ownership and technology reallocation.

This causal effect of common ownership on the reallocation of technologies can result from various mechanisms. The ways in which common shareholders may influence the selection of adopters correspond to different frictions in the market for ideas. By alleviating these frictions, common ownership linkages can improve the total surplus of engaging in technology transfer, thereby affecting the matching of adopters to providers. To identify the specific mechanism by which common ownership affects this matching, I analyze a simple model of the market for technology and test further hypotheses derived from this model.

Theoretically, my analysis suggests that common ownership can impact the reallocation of technologies by affecting managerial incentives. The presence of common shareholders alleviates the moral hazard linked to the transfer of uncodified know-how: A technology transfer often entails both, trades of intellectual property rights and transfers of innovative know-how that is not

[1] Akcigit, Celik and Greenwood (2016) show that search and matching frictions in technology markets create substantial welfare costs. Other studies emphasize the importance of agency problems between the partners involved in the transfer of knowledge, decreasing the potential surplus of these transfers (e.g., Contractor and Sagafi-Nejad, 1981; Macho-Stadler, Martinez-Giralt and Pérez-Castrillo, 1996; Choi, 2001).

fully evident in the reassigned patents (i.e., uncodified or tacit know-how; see, e.g., Arora, 1995; Macho-Stadler, Martinez-Giralt and Pérez-Castrillo, 1996). Common ownership can incentivize managers of the technology provider to transfer valuable know-how, which can enhance the quality of technology transfer and increase the benefits of technology adoption. Adopters' management anticipates this positive effect of common ownership and can leverage it to increase the surplus from engaging in the deal compared to situations with less common ownership among the parties involved. Therefore, an adopter with more common ownership linkages to the technology provider enjoys an advantage over other potential buyers of the technology. This relationship between common ownership and the surplus generated by the transfer results in the likelihood of two firms matching in the market for technology to increase with common ownership between these firms.

Empirically, I test if the evidence supports my model. First, if the effect of common ownership on adopter selection is a result of alleviating moral hazard in the transfer of uncodified know-how, the effect should be stronger for technologies that require such transfers to make their adoption beneficial for the acquirer. Indeed, the data confirm that the effect of common ownership is stronger for technology transfers associated with more recent innovations, for which less know-how is codified. Similarly, I find evidence that the effect of common ownership is also stronger if more complex technologies are reassigned. In both cases, the moral hazard problem linked to transfers of uncodified know-how is more severe. Thus, common ownership has a more substantial effect on the transfer quality resulting in a stronger impact on adopter selection. Second, the model predicts an increase in transfer quality if common ownership between the provider and adopter is larger. The data show that conditional on a technology transfer occurring, adopters create more, and in total, more valuable, innovations in the future when the common ownership incentives for the provider with respect to the adopter are stronger. Adopters receiving higher-quality transfers due to common ownership can better exploit new ideas and benefit more from the reassignment. Moreover, both the adopter and common owners of the assignor and assignee benefit financially since, through the higher transfer quality, common ownership positively affects the adopter's future market capitalization growth after a transfer has occurred. These findings strongly support my theory.

Akcigit, Celik and Greenwood (2016) show that search frictions can impede technology transfer, and reducing such frictions could lead to significant welfare gains. As such, it is possible that common ownership affects the reallocation of intellectual property rights by reducing search frictions. Diversified institutions may achieve this by leveraging their extensive networks. However, this may entail monitoring potential opportunities for profitable technology reallocation among portfolio firms, which can be costly. To test this alternative explanation, I use data from Guo, Pérez-Castrillo and Toldrà-Simats (2019) on financial analyst coverage. The results indicate that the effects of common ownership are not more pronounced for potential adopters that are less prominent in the market. Therefore, my baseline findings are unlikely explained by the reduction of search frictions.

Furthermore, recent literature cites a link between common ownership and interlocking directorates (Nili, 2019, 2022; Fletcher, Peitz and Thépot, 2022), and Azar (2022) specifies that greater common ownership between two firms also tends to imply a greater likelihood that they share directors. When I exclude dyads with common directors from the sample, I still find a significant effect of common ownership on the reallocation of technologies. That is, the impact of common ownership is not the result of board connections. If I also control for directors' roles in the two boards, I find that non-executive directors serving on both boards do not increase the probability of technology transfers, consistent with previous findings related to directors who serve on multiple boards or the "busy directors" (Fich and Shivdasani, 2012; Hauser, 2018). But *executive* directors who also serve on the other company's board enhance the probability that the two firms will match in the market for technology.

Cai and Sevilir (2012) study the effect of board connections on M&A transactions. To the best of my knowledge, the current study is the first to investigate the interaction of common ownership with joint directors that serve as executives in one of the firms, to identify the incentives induced by these conditions, and to outline the consequences for corporate strategy. With this novel approach, I can establish that executives of technology providers that also serve as directors on the board of potential adopters have similar incentives to internalize the profits of the latter firm as those managers of patent assignors that share common owners with potential adopters. Hence, the two determinants of technology transfer are substitutes in determining matches. In contrast, when an executive of a potential adopter also serves on the board of the technology provider, it can increase the likelihood of technology transfer too, but for different reasons. Due to their presence on the providers' board, they enjoy advantages in acquiring information about the available technology and its technological fit with their (adopter) firm. In this way, they help overcome adverse selection issues, which also grants them a bargaining advantage (Cai and Sevilir, 2012). Consistent with this reasoning, the effects of common ownership and executives of adopters that sit on the provider's board are complementary.

My analysis contributes to the literature on common ownership (Rotemberg, 1984; Azar, 2017) and its relationship with corporate innovation (López and Vives, 2019; Vives, 2020; Antón et al., 2021*b*). In particular, it considers know-how transfers in voluntary interactions in markets for technology rather than addressing exogenous or unintended knowledge spillovers. Thus I can detail the role of information asymmetries between providers and adopters in the relationship between common ownership and firm matching, as well as clarify that the extent to which adopters benefit from technology transfers depends on the managerial incentives of provider-managers, as induced by common ownership or interlocking directorates. Although I analyze the impact of these phenomena in the context of patent reassignments, the identified mechanisms are likely to apply also to other modes of technology transfer, such as licensing.

To establish these insights, Section 1 contains a detailed outline of the data, variables, and sample selection process. Section 2 outlines the empirical strategy. Section 3 presents the baseline results regarding the effect of common ownership on technology reallocation. To explain these results, I detail the relevant theory and analyze the model in Section 4, from which I derive further hypotheses. I test these hypotheses in Section 5. Then with Section 6, I investigate if common owners reduce search frictions, followed by a consideration of the impact of interlocking (executive) directorates in Section 7. Finally, Section 8 concludes.

# 1 Data, Variables, and Sample Construction

In addition to presenting the data sources used to construct the variables, I outline how I created the data set in this section.

## 1.1 Data

The sample includes U.S. public firms with information available between 1990 and 2006. Their financial information came from Compustat; I exclude financial firms and utilities (standard industrial classification [SIC] codes 4000-4999 and 6000-6999), as well as firms with total assets less than $10 million. For information on patent reassignments, I turn to the USPTO Patent Assignment Data Set, which contains the names of assignors and assignees linked through a patent ownership transfer. Similar to Akcigit, Celik and Greenwood (2016), I rely on an algorithm to clean the names of these parties, such that they reflect the names of the actual USPTO patent assignees.[2] Thus I can match firms in the reassignment data set with those in Compustat, using the dynamic matching procedure available in the National Bureau of Economic Research (NBER) patent database.

The Thomson Reuters Institutional Holdings (form 13F) database provides institutional ownership information, so I use it to construct a pertinent explanatory variable, namely, the profit weight measure of common ownership (as described in the next section). For the period 1990-2006, I can obtain information about the number of outstanding shares and shares held by institutional investors for each firm. However, because this 13F data set suffers several data quality issues, I manually cleaned the data by removing duplicate observations and incorrectly assigned holdings information, as well as replacing missing information with information available from the Center for Research in Security Prices and Compustat. After this cleaning, I aggregated fund holdings at the institutional investor level.[3] For several alternative common ownership measures, I also turn to Wharton Research Data Services, which provide measures from Gilje, Gormley and Levit (2020).[4]

The R&D expenses are available from Compustat. I collect patent and citation information for 1990-2006 from the NBER patent citation database (Hall, Jaffe and Trajtenberg, 2001), but I also extend these data by leveraging the Harvard Business School patent database, which provides information about patents and citations up until 2010. Following Hall, Jaffe and Trajtenberg (2001) and Atanassov (2013), the "time-technology class fixed effect" method, applied to relevant specifications, helps address truncation problems for patent and citation outcomes. With the patent and citation information, I construct measures of firms' innovativeness, distance to a reassigned technology, as an inverse measure of technological propinquity (Akcigit, Celik and Greenwood, 2016); and future innovation activity after a potential technology transfer.

[2]In their Internet Appendix, Akcigit, Celik and Greenwood (2016) provide further details about this name matching process.

[3]Some large institutional investors, such as BlackRock, report holdings disaggregated to the asset manager level. I take this possibility into account and aggregate such information when necessary, using the method suggested by Gilje, Gormley and Levit (2020).

[4]I thank these authors for providing their data sets, which facilitate research on common ownership and its impact on managerial incentives.

Coverage by financial analysts is defined using data from Institutional Brokers Estimate Systems (I/B/E/S). The firm-level variable comes from Guo, Pérez-Castrillo and Toldrà-Simats (2019).[5] Data about corporate boards and common directors come from BoardEx. Finally, to construct the instrumental variable, I use ownership data for pure indexer mutual funds that own publicly traded companies, which are available in the Thomson Reuters mutual fund data set (S12). To identify pure indexer funds, I rely on information from Petajisto (2013).[6]

## 1.2 Variables

Table 1 contains a complete list of the variables used to analyze the link between common ownership and patent reassignments, along with their definitions, as further specified hereafter.

*Dependent Variable.*—To analyze how common ownership influences the probability that two firms engage in technology transfers, I use a binary outcome as the primary dependent variable. That is, the indicator variable $Reass_{AB,r}$ takes a value of 1 if firm $A$ transfers the reassignment $r$ to firm $B$ in a given year and 0 otherwise. A reassignment $r$ involves any transfer of ownership of a bundle of patents at a given execution date. Next, I define the main *independent variables.*

[Table 1 about here.]

*Profit Weight.*—A natural measure of common ownership is the profit weight that an assignor attributes to the profits of a potential assignee. This measure also has been used widely in prior theoretical and empirical studies of common ownership (e.g., López and Vives, 2019, and Backus, Conlon and Sinkinson, 2019).[7] The profit weight measure can be derived from a Pareto problem, with the assumption that a firm manager seeks to maximize the weighted average of shareholders' wealth (Rotemberg, 1984). The Pareto weights a manager assigns to each investor are unobservable, so prior literature suggests assuming proportional control (e.g., Azar, Schmalz and Tecu, 2018), limited to shareholders that hold at least 1% of the focal firm's outstanding shares.[8] Therefore, the primary measure of the common ownership incentives of firm $A$ with respect to firm $B$ can be calculated as follows:

$$\kappa_{1\%,AB} = \frac{\sum_i \beta_{iA}\beta_{iB}}{\sum_i \beta_{iA}^2}, \tag{1}$$

where $i = 1, 2, 3, \ldots$ indexes shareholders, and $\beta_{ij}$ is the share of stocks hold by shareholder $i$ in company $j \in \{A, B\}$.

[5] I thank these authors for sharing their data.

[6] I thank this author for providing these data on his webpage, https://www.petajisto.net/data.html.

[7] This measure also constitutes a component of the $MHHI$ (O'Brien and Salop, 2000) and $MHHI\Delta$ measures, as used in studies of potential anticompetitive effects of common ownership (e.g., Azar, Schmalz and Tecu, 2018). In contrast with those studies, I do not use market share weighting, which creates a potential source of endogeneity in common ownership measures. My analysis, at the dyadic level, avoids this concern.

[8] By focusing only on shareholders with more than 1% ownership, the measure is less likely to become very skewed. The denominator of the measure is the sum of squares of investors' ownership in firm A, so including investors with tiny holdings would lead to assignments of huge profit weights to firms with a single common owner that holds a small share in firm $A$ and a substantial share of firm B, even though this owner cannot effectively influence firm $A$'s corporate strategy or managerial incentives. The baseline results, estimated with a probit model, also prove robust to including all shareholders.

*GGL Measures.*—Institutional investors, including common owners, may adopt different monitoring practices toward the managers of firms in their portfolios, which in turn could be relevant for understanding the effects of common ownership on technology transfer. Therefore, I include another common ownership measure (Gilje, Gormley and Levit, 2020), which accounts for investors' portfolio weights as proxies of the attention an investor grants to a firm. These measures are computed as follows:

$$GGL_{AB} = \sum_i \beta_{iA} g(\rho_{iA}) \beta_{iB}, \tag{2}$$

where $i$ refers to investors; $A$ and $B$ are two different firms; and $\beta_{iA}$ and $\beta_{iB}$ are the shares of equity held by investor $i$ in firms $A$ and $B$, respectively. The weight of firm $A$ in investor $i$'s portfolio is $\rho_{iA}$, that is, the ratio of the value of the investment in firm $A$ to investor $i$'s total assets under management. Thus, the function $g(\cdot)$ proxies for the probability that an investor pays close attention to firm $A$'s management's decisions. Intuitively, a manager's incentives to internalize the common ownership interests of an investor $i$ increase with the shares held by this investor ($\beta_{iA}$), as well as with the ownership share of the investor in the other firm ($\beta_{iB}$), which influences the extent to which manager $A$'s decisions affect investor $i$'s portfolio value, through its effect on firm $B$'s profits. Finally, this measure increases with the probability ($g(\rho_{iA})$) that the investor pays attention to the manager's decisions. Because this set of measures can be derived from a model of a managerial agency problem, they can be interpreted as indicators of managerial incentives to internalize the effect of corporate strategies on other firms' profits.

The GGL class of measures also is flexible enough to accommodate different assumptions about the functional form of $g(\cdot)$, reflecting how investor attention might depend on the portfolio weight of the firm. Gilje, Gormley and Levit (2020) compute their measures using different assumptions about $g(\cdot)$. In particular, they propose versions that feature *full attention* ($g(\rho_{iA}) = 1$), along with *linear* ($g(\rho_{iA}) = \rho_{iA}$), *concave* ($g(\rho_{iA}) = \rho_{iA}^{1/2}$) , and *convex* ($g(\rho_{iA}) = \rho_{iA}^2$) specifications for $g(\cdot)$. They also fit a version of $g(\rho_{iA})$ to the likelihood that an investor vote fails to follow the recommendations of the proxy advisor *International Shareholder Services*, which provides a proxy of the independence of the investor's decision-making relative to the firm's strategy and, thus, of the investor's attention.[9] The fitted attention function reveals a concave relationship between portfolio weights and investor attention; Gilje, Gormley and Levit (2020) use it to construct another version of their measure, $GGL_{\text{fitted}}$.[10] Gilje, Gormley and Levit (2020) also scale the measures by the sample average, such that a value of 1 indicates an average level of incentives.

*Technological Distance.*—To control for the technological propinquity of the reassigned technology to a potential assignee, I construct a measure of the technological distance between the bundle of patents being sold and the patent stock already held by potential buyers. Similar to

[9]This approach reflects evidence from Iliev and Lowry (2015) on the relationship of the portfolio weight and investors' independent voting behavior. Proxy advisory firms are often accused of giving "blanket recommendations" or following a one-size-fits-all approach (see also Coles, Daniel and Naveen (2008) and Johnson, Karpoff and Yi (2015) for illustrative evidence that such approaches might not be optimal, regarding to the board size and takeover defenses, respectively). If investors increase their attention to a given firm in their portfolios, they likely gather information and form independent opinions about the corporate proposals on which they have to vote. Thus, they are less likely to follow blanket recommendations of a proxy advisor.

[10]Gilje, Gormley and Levit (2020) provide further details on the construction of this measure.

Akcigit, Celik and Greenwood (2016), I construct the distance metric on the technology space; the measure of technological distance pertains to an individual patent and firm. Then I can aggregate the distances of each patent in the reassigned bundle. Akcigit, Celik and Greenwood (2016) also show that a patent contributes more to firm value when its distance from the firm's location in the technology space is smaller.

The distance between two 2-digit International Patent Classification (IPC) technology classes $X$ and $Y$ is given by

$$d(X,Y) = 1 - \frac{||(X \cap Y)||}{||(X \cup Y)||}, \tag{3}$$

where $||(X \cap Y)||$ is the number of patents that cite patents from both classes, and $||(X \cup Y)||$ is the number of patents that cite one or the other class (or both). Therefore, the distance between a technology class and itself is $d(X,X) = 0$; likewise, $d(X,Y) = 1$ if no patent cites both IPC technology classes. With this metric, I construct the distances of individual patents from a firm's patent portfolio in a given year. A firm's patent portfolio in a given year contains all patents it applied for up to that year. The distance between a patent and a firm is given by

$$d_\iota(f,p) = \left[\frac{1}{||\mathcal{P}_f||} \sum_{p' \in \mathcal{P}_f} d(X_p, Y_{p'})^\iota\right]^{\frac{1}{\iota}}, \tag{4}$$

where $p$ is a patent, $f$ identifies the firm, and $\mathcal{P}_f$ is the firm's patent portfolio. As Akcigit, Celik and Greenwood (2016) suggest, I set $\iota = 2/3$.

As mentioned previously, I aggregate the measure across all patents $p \in \mathcal{R}$. The bundle $\mathcal{R}$ refers to the set of patents in reassignment $r$. The technological distance measure also weights the patents in the reassignment $r$ by citations:

$$d_{f,r} = \sum_{p \in \mathcal{R}} d_\iota(p,f) w_p, \tag{5}$$

where $w_p$ is the weight of each patent, equivalent to the number of citations the patent received up until 2010, scaled by the average number of citations of patents in the same application year and technology class, divided by the sum of this statistic for all patents in the reassignment. Therefore, $\sum_{p \in \mathcal{R}} w_p = 1$.[11]

*Board Connections.*—To account for connected corporate boards or interlocking directorates, I construct an indicator variable, $CD_{AB}$, that takes a value of 1 if a common director serves on the boards of both firms, $A$ and $B$. To account for the different roles common directors might take on two distinct boards, I also construct two indicators, $ExecCD^A_{AB}$ and $ExecCD^B_{AB}$, that equal 1 if the common director is an executive of firm $A$ or $B$, respectively, and 0 otherwise.

*Control Variables.*—I control for several firm characteristics. First, the measure *InstOwn* addresses total institutional ownership (i.e., the share of stocks held by all 13F institutions in a firm).

[11] Several robustness checks related to the aggregation method, shifted to the patent bundle-firm level, include equal weighting or assigning greater weights to the most recent or most cited patent. The main results are robust to these different weighting techniques and remain qualitatively the same (Hutschenreiter, 2022).

Second, I include a measure of the firm's patent stock, *Pstock*. As in Arqué-Castells and Spulber (2021), this measure equals the natural log of (1 +) the prior 5-year average of eventually granted patent applications. It thus accounts for firms' long-run innovativeness, patenting experience, and absorptive capacity.

Furthermore, I control for *FirmSize*, which is the natural logarithm of total assets; *R&DtoAssets*, which corresponds to R&D expenses scaled by total assets; *FirmAge*, or the number of years the firm has existed, according to Compustat; *Leverage*, which is the ratio of firm debt to total assets; *CashtoAssets*, corresponding to firms' cash scaled by total assets; *Profitability*, which is the return on equity; *Tobin's Q*, to gauge the firm's growth potential; *PPE*, computed as firms' property, plant, and equipment, scaled by total assets; *CapextoAssets*, which corresponds to firms' capital expenditures scaled by total assets; *MarketCap*, which measures the firm's market capitalization at the fiscal year end; and the *KZindex*, a measure of financial constraints (Kaplan and Zingales, 1997). Another variable that can influence corporate innovation is the number of financial analysts that issue forecasts for a firm. Therefore, I control for the natural logarithm of (1 +) the number of financial analysts, or *AnalystCoverage*.[12] Aghion et al. (2005) also argue that product market competition affects innovation, through an escape competition and a Schumpeterian effect, and that the resulting combined effect may be nonlinear. The impact of competition on technology adoption also may be nonlinear. Therefore, I include *HHI*, which is the Hirschman-Herfindahl index based on market shares, to measure industry concentration, along with its squared value $HHI^2$, as additional controls. With an index of corporate governance *CGIndex*, I adopt an approach similar to the one suggested by Bertrand and Mullainathan (2001), García-Lara, García-Osma and Penalva (2009), and Guo, Pérez-Castrillo and Toldrà-Simats (2019). Finally, to mitigate the effect of outliers, I winsorize *Profitability*, *Tobin's Q*, and the *KZIndex* at the 1st and 99th percentiles.

*Instrumental Variable.*—To account for the potential endogeneity of common ownership, I construct the instrumental variable $PassOwnInstrument_{AB}$ as the percentage ownership of firm B's outstanding shares by pure indexers that also track indexes in which firm $A$ is a constituent. Pure indexer funds are those mutual funds that track the *S&P 500*, *Russell 1000*, *Russell 2000*, or *Russell Mid Cap* index and for which the sum of the differences between the funds' portfolio positions and the weights of firms in the index is less than 5% (Petajisto, 2013).

In detail, following Schmidt and Fahlenbrach (2017), I identify index-tracking mutual funds in the Thomson Reuters (S12) mutual fund data set, according to the categorization and data from Petajisto (2013) that detail which mutual funds benchmark against which stock market index. Petajisto (2013) also measures how closely the index trackers replicate the benchmark index portfolio. This measure, *ActiveShare*, is defined as

$$ActiveShare = \frac{1}{2}\sum_{i=1}^{N} |w_{Fund,i} - w_{Index,i}|, \tag{6}$$

where $w_{Fund,i}$ is the weight of stock $i$ in the fund's portfolio, $w_{Index,i}$ is the weight of the same stock in the fund's benchmark index, and the sum gets computed across the universe of all assets. Notably, *ActiveShare* is the percentage of the fund's portfolio that varies from the fund's benchmark

[12] Guo, Pérez-Castrillo and Toldrà-Simats (2019) offer detailed information about how to construct this variable. I thank these authors for providing the data.

index. With this measure, I can identify the funds that closely track one of the four indexes, with $\mathit{ActiveShare} < 5\%$.[13] Next, for each potential assignee in the data set, I compute passive ownership of the funds separately, for each of the four benchmarks, $\mathit{PassOwn}_{B,\mathit{Index}}$. Combining these data at the dyad, I derive the following instrument:

$$\begin{aligned} \mathit{PassOwnInstrument}_{AB} = \;& \mathbf{I}_{A,\mathit{S\&P500}} \times \mathit{PassOwn}_{B,\mathit{S\&P500}} \\ & + \mathbf{I}_{A,\mathit{Russell1000}} \times \mathit{PassOwn}_{B,\mathit{Russell1000}} \\ & + \mathbf{I}_{A,\mathit{Russell2000}} \times \mathit{PassOwn}_{B,\mathit{Russell2000}} \\ & + \mathbf{I}_{A,\mathit{RussellMC}} \times \mathit{PassOwn}_{B,\mathit{RussellMC}}, \end{aligned} \tag{7}$$

where $\mathit{PassOwn}_{B,\mathit{Index}}$ is passive ownership of pure index funds in firm $B$ that follow a particular, given index, and $\mathbf{I}_{A,\mathit{Index}}$ is an indicator variable that takes the value of 1 if firm $A$ is a constituent of the given index. I establish this instrument's validity when outlining the empirical strategy in Section 2.2.

## 1.3 Sample construction and descriptive statistics

In the constructed data set, at the dyad-technology level, each observation is a dyad of firms that may trade a particular technology, reflecting the bundle of patents reassigned at a given execution date within a particular year during the sample period (1990-2006). To develop this data set, I first collected all dyads of an assignor and actual assignee that trade a bundle of patents. Then, similar to Bena and Li (2014), I add potential counterfactual pairs in the technology market. These counterfactual pairs consist of the same assignor but different assignees. The actual assignor remains the unique supplier of the reassigned bundle of patents and technological know-how; keeping this technology provider constant for a given deal across real and counterfactual trading firm pairs allows to control for the technology-assignee match characteristics, including the technological distance between the patent bundle and the patent stock of the (actual or counterfactual) assignee.

To construct the counterfactual observations, I pair the actual assignor with firms that could have engaged in the transfer of intellectual property, as an alternative adopter of the technology. The selection process features a few criteria. First, the counterfactual adopter must be a publicly traded company, active in the year of the deal. Second, it must operate in the same 2-digit SIC industry as the actual adopter.[14] Third, all pairs in the sample must include firms that have been granted at least one patent prior to the year of the deal, which is necessary to gauge their technological propinquity. In addition, to control for differences in innovation intensity, I use the patent stock (*Pstock*) and innovation expenses (*R&DtoAssets*) of all potential assignees, that is,

[13] When I vary the active share between 1% and 20%, the results remain robust. However, as is reasonable, if I were to use only those funds with an active share close to 0, the instrumental variable regression suffers from weak identification for some common ownership measures. Only a few funds track each position of the index perfectly, considering their need to include transaction costs when making adjustments due to fund in- or outflows or index reconstitutions. The 5% cutoff thus seems reasonably close to a perfect portfolio replication of the index.

[14] This criterion helps limit the overall number of observations. Furthermore, it is plausible that an invention can be beneficially employed in one sector of the economy but not others. I use a broad industry definition (2-digit SIC) to avoid excluding suitable alternative adopters though.

all actual and counterfactual assignees. The resulting sample, including all possible counterfactual pairs that satisfy these criteria, consists of 19,179 dyadic observations, of which 191 firm pairs trade patents. Thus, the unconditional probability that a potential assignee is the actual buyer of patents is approximately 1%.

[Table 2 about here.]

Table 2 contains summary statistics for the 191 actual technology adopters (assignees) in the technology market between 1990 and 2006; Table 3 provides a comparison of the summary statistics for actual versus counterfactual assignees, along with the firm characteristics of the patent assignors. On average, the common ownership measures are consistently greater for the actual assignees than for the counterfactual firms. Similarly, the technological distances are smaller for actual assignees than for the entire set of control firms, indicating that these actual assignees are technologically closer to the reassigned bundle of patents than the control group is. The average patent stock of actual assignees also is greater than that of the counterfactual adaptors, suggesting differences in their absorptive capacity. The actual assignees exhibit greater institutional ownership too, which I control for in all the regressions. Finally, actual assignees, on average, are larger, older, and have more growth potential. Besides the means of these variables, Table 3 also lists their minimal and maximal values; the control group observations reveal a wide range of these characteristics suggesting that it serves as a suitable control. Because the actual and counterfactual assignees differ on average, I also constructed two matched samples, then repeated the baseline analysis. The results, reported in the Online Appendix, confirm that the results of my baseline analysis presented in this paper are robust to selecting a matched subset of control group observations.[15]

[Table 3 about here.]

Finally, Table 4 offers correlation coefficients across different common ownership measures. The correlations between the profit weight $\kappa_{1\%,AB}$ and each of the GGL measures all are below 0.5. By ordering the GGL measures by decreasing correlation with the full attention version, I demonstrate that the more convex the assumed relationship between the assignor's weight in the portfolio of the investor, the lower the correlation of the corresponding measure with the full attention version. The more convex measures more powerfully overweight the effect of investors with high portfolio weights, relative to other investors. Although $GGL_{\text{Fitted},AB}$ and $GGL_{\text{Concave},AB}$ correlate with $GGL_{\text{FullAttention},AB}$ at 0.901 and 0.582 levels, respectively, the correlations of the latter with $GGL_{\text{Linear},AB}$ and $GGL_{\text{Convex},AB}$ reach only 0.382 and 0.285, respectively.

[Table 4 about here.]

[15] See Section 1 of the Online Appendix.

# 2 Empirical Strategy

## 2.1 Probit regressions

To learn which pairs of firms engage in technology transfer and how common ownership affects the matching in the market for technology, I estimate the coefficients of the independent variables in a sample of cross-sections of actual dyads that engage in technology transfer, as well as control pairs constructed from actual assignors and counterfactual assignees. Similar to Banal-Estañol, Macho-Stadler and Pérez-Castrillo (2018) and Arqué-Castells and Spulber (2021), I estimate a probit model given by

$$\begin{aligned} Reass_{AB,rtj} = \beta_0 + \beta_1 CO_{AB,(t-1)j} + \beta_2 d_{B,rtj} + \beta_3 CD_{AB,tj} \\ + \delta X_{B,tj} + \eta_{A,rtj} + u_{AB,rtj}, \end{aligned} \tag{8}$$

where $A$ indicates the actual seller of a technology (assignor), $B$ refers to potential buyers (assignees), and $r$ reflects the bundle of patents reassigned from firm $A$ to some firm $B$ in year $t$. The subscript $j$ indicates firm $B$'s 2-digit SIC code, which is the same across all observations of a given deal, defined as the group of observations corresponding to a given technology assignor $A$ selling a given bundle of patents $r$ on a given execution date in year $t$. The dependent variable of the binary outcome model, $Reass_{AB,rtj}$, equals 1 if firm $A$ sells technology $r$ to firm $B$ in year $t$ (actual traders) and 0 otherwise (counterfactuals). Then $CO_{AB,(t-1)tj}$ represents one of the measures used to gauge common ownership at the last quarter of year $t-1$. The technological distance between potential assignees and the reassigned technology is captured by $d_{B,rtj}$, and $CD_{AB,tj}$ indicates whether the boards of firms $A$ and $B$ share a common director. In turn, $X_{B,tj}$ is a vector of firm characteristics, and $\eta_{A,rtj}$ is the deal-fixed effect (Bena and Li, 2014). I cluster the standard errors at the deal level $r$.

As mentioned previously, I also construct matched samples. Matching counterfactual pairs that are similar to actual traders in the technology market provides a more balanced sample and helps control for potential confounders. When I estimate the same probit model, using the observations in the matched samples, it produces results that are very similar to the baseline results shown in Section 3. Therefore, I detail the matched sample results in the Online Appendix (Section 1) and briefly discuss them in conjunction with the baseline results in Section 3.

The estimation of the effect of common ownership on reassignments might be biased by reverse causality or omitted variables. For example, institutional investors might invest more frequently in innovative firms, and these firms could exhibit a greater propensity to trade patents, which would lead to a spurious relationship between common ownership and patent trades. Therefore, I control for firm-level innovativeness, using average patents granted per year (*Pstock*) and research intensity (*R&DtoAssets*) measures. I also include the percentage of ownership held by institutional investors (*InstOwn*) and firms' growth potential (*Tobin's Q*) in all regressions, to address the potential upward bias in the coefficient of common ownership. Because reverse causality also could occur if institutional investors anticipate a positive surplus from a patent trade shared by trading partners, such that they proactively invest more in one or both firms participating in the deal, I rely on lagged variables. In detail, I measure common ownership in the last quarter of year $t-1$ to predict reassignments in year $t$. Finally, to address potential endogeneity further, I estimate an instrumental variable (IV) model, as described next.

## 2.2 Instrumental Variable Strategy

With regard to the IV, I estimate Equation (8) by instrumenting the common ownership measures. The instrument's construction reflects Equation (7) in Section 1.2; it measures passive ownership of the stock of firm $B$ (assignee) by pure indexer funds[16] that track the indexes of which firm $A$ is a constituent. As for the common ownership measures, I use passive ownership in the last quarter of year $t-1$ to instrument $CO_{AB,(t-1)j}$.

*Relevance.*—This instrument is relevant. First, for a given deal, the assignor remains the same across all observations, so the only way common ownership between the assignor and potential assignees can vary within a deal-group is with a difference in investors and ownership shares in potential assignees. Second, for pure indexers, in principle, a fund can be a common owner of two firms only if both of them are members of the particular index that the fund tracks.[17] Third, passive funds that track an index by investing in (almost) all its constituents are the most diversified investors among the subset of index constituents, so they should contribute most to the common ownership linkages of a given firm. Fourth, passive funds that do not engage in stock picking but rather replicate the index portfolio may be non-passive owners in the sense that they engage with and influence management, as I discuss subsequently. Fifth, the instrument accounts for the varying numbers of pure index funds that operate in the market over time and attract investments from clients. Thus, the funds have a variety of assets under management, which allows for changing potential to own smaller or larger shares in the index constituents over time.

*Exclusion Restriction.*—The instrument also satisfies the exclusion restriction. First, pure indexers cannot select firms to over- or underweight in their portfolio, relative to the index (e.g., because they are more or less innovative) without increasing their active share. Therefore, I determine the passive ownership of pure indexers with an active share of less than 5%. Second, I consider different stock market indexes that are market cap-weighted but represent different market segments. The *Russell 1000* index consists of 1000 companies with, roughly, the highest market capitalization in the U.S. economy. The *S&P 500* contains roughly the first half of the *Russell 1000* index. The *Russell Mid Cap* comprises 800 smaller firms from the *Russell 1000*. Finally, the *Russell 2000* contains the largest 2000 firms that are not constituents of the *Russell 1000*. By using different indexes, I can address the concern that common ownership and the instrument actually might be determined by a firm's market capitalization or its ranking relative to other firms in the same index. When combining firms' membership in the different stock market indexes, the passive ownership of indexer funds must be random and unrelated to market capitalization

[16]See also footnote 13 on Page 10.

[17]This point may raise a concern that the estimated effect of common ownership on reassignments is driven by index inclusion. Firms and potential assignees could be more salient to providers if they are constituents of a certain stock market index. I address this concern in two ways. First, I identify variation in common ownership between firms within indexes by leveraging passive ownership, instead of (joint) index inclusion, as an instrument. Second, as a robustness check, I run the baseline IV regression but add index-constituent fixed effects, in the form of an indicator for each index that takes a value of 1 if a potential adopter is a member of the index and is 0 otherwise (untabulated). The results remain robust; the effect of common ownership is still positive and highly significant.

or other firm characteristics (e.g., innovativeness).[18] Third, the focus on pure indexers alleviates concerns about reverse causality, because even if index funds could anticipate potential gains from technology transfers involving portfolio firms (which is very unlikely; it would demand vast information acquisition and constant monitoring efforts), it remains difficult for them to reallocate their investments to the firms before they engage in the transfer without increasing their active share.[19] Otherwise, future technology transfers would have predictive power for past passive ownership of funds with active shares smaller than 5%. To rule out this possibility, I ran regressions of pure indexers' passive ownership in the last quarter of year $t-1$ on the dummy variable $Reass_{AB,rtj}$, with and without all control variables and year and firm fixed effects, using a panel of all firms in the sample of potential assignees from Compustat. In these regressions (see Section 2 and Table 5 in the Online Appendix), the coefficient of $Reass_{AB,rtj}$ is negative, close to 0, and not statistically significant at any usual level ($p$-values ranging from 0.673 to 0.844). Thus, reassignments are unlikely to affect past common ownership by the funds in the last quarter of the year prior to the reassignments. In turn, the IV estimates do not appear biased, due to either reverse causality or for any other source of endogeneity.

Even acknowledging these features though, two concerns might arise regarding the validity of this IV. First, passive ownership might involve only a small subset of institutional ownership, such that it accounts for a tiny portion of common ownership linkages and induced incentives. However, as Banal-Estañol, Seldeslachts and Vives (2022) show, passive investors are more diversified than active institutional investors. When they decompose the profit weights, they demonstrate that more passive, relative to active, ownership consistently increases the implied product market incentives induced by common ownership, resulting in higher markups.

Second, passive investors might be inactive in terms of monitoring, influencing, and engaging with management. Thus, the common ownership correlation with the instrument might not translate into actual changes in managerial incentives, corporate behavior, or strategy. Evidence related to passive investors' involvement in corporate governance and managerial behavior is mixed. On the one hand, Appel, Gormley and Keim (2016) find that passive mutual funds influence firms' governance choices, resulting in more independent directors, removal of takeover defenses, and more equal voting rights. On the other hand, Schmidt and Fahlenbrach (2017) indicate that exogenous increases in passive ownership lead to greater CEO power and diminished corporate governance, in which case passive funds may be less attentive to corporate governance or consider it too costly to participate in firm-specific decision-making and monitoring of management decisions. Schmidt and Fahlenbrach (2017) offer an explanation, noting that Appel, Gormley and Keim (2016) focus on low-cost governance activities that entail minimal consistent monitoring by institutional investors. But with regard to costly governance activities, passive ownership may affect corporate governance negatively and reduce shareholder value.

[18]I reestimated the baseline IV model, including firms' market capitalization as a control variable in a robustness check (untabulated). The coefficient for market capitalization is not statistically significant. The coefficients of common ownership are qualitatively and quantitatively similar to those in the baseline IV regressions. I also estimated the IV model with assignees' market capitalization, the squared market cap, the ratio of market caps of the potential assignee and assignor, and the square of this ratio (untabulated). These results also are robust with regard to the coefficients of common ownership.

[19]Recall that I use lagged variables.

For the current study, I anticipate that common ownership does not influence the matching in the market for technology by institutions that constantly search for profitable reallocations of technologies (a high-cost activity). But my focus is on the situation after a potential match has been formed, in which setting I predict they leverage the degree to which the deal is profitable by increasing the transfer quality in a low-cost way, such as engaging with the provider's management in informal conversations (e.g., to ensure the provision of technological services facilitating the adoption of the technology). This intervention by institutional investors should then be anticipated by the technology adopters' management, such that it shapes the matching in the market for technology. In turn, the costs of acquiring information arguably would be borne by adopting firms (rather than investors) that have incentives to share information with common owners, which helps them ensure a more efficient transfer of innovative knowledge. Whether the intervention of common owners in technology transfers is more or less costly for the investors compared to simple governance interventions is unclear. I account for this by using different common ownership measures that vary with regard to the assumptions on the monitoring incentives of heterogeneous investors.

Finally, it is worth noting that Shekita (2022) has documented interventions by common owners, based on various sources. Some interventions come from institutions that mainly offer passive index funds and index ETFs. The interventions that lead to better quality know-how transfers are notably less visible to the public, less general, and inclusive of a smaller set of firms than those that Shekita (2022) identifies. Nevertheless, this evidence indicates that passive institutional common owners are willing to shape managerial decisions actively.

Therefore, the IV model that I estimate includes the following first-stage regression:

$$\begin{aligned} CO_{AB,(t-1)j} = \alpha_0 + \alpha_1 PassOwnInstrument_{B,(t-1)j} + \alpha_2 d_{B,rtj} \\ + \alpha_3 CD_{AB,tj} + \alpha_4 X_{B,tj} + \eta_{A,rtj} + \varepsilon_{AB,rtj}. \end{aligned} \tag{9}$$

Then in the second stage, I estimate the following probit model:

$$\begin{aligned} Reass_{AB,rtj} = \beta_0 + \beta_1 \widehat{CO}_{AB,(t-1)j} + \beta_2 d_{B,rtj} + \beta_3 CD_{AB,tj} \\ + \delta X_{B,tj} + \eta_{A,rtj} + u_{AB,rtj}, \end{aligned} \tag{10}$$

where $\widehat{CO}_{AB,(t-1)j}$ denotes the predicted values of the first-stage regression.

# 3 Baseline Results: The Effect of Common Ownership on Assignee Selection

In this section, I present the baseline results, based on estimates of the effect of common ownership on the matching in the market for ideas. That is, I test the following main hypothesis:

**Hypothesis 1.** *Greater common ownership between an assignor and a potential assignee increases the probability of a technology transfer between these firms.*

To do so, I follow the identification strategy outlined in Section 2.

*Probit Model.*—Table 5 contains the baseline results for the simple probit model from Equation (8), according to the sample described in Section 1.3. Each column indicates the coefficient for a different measure of common ownership. That is, Column (1) presents the coefficient for the profit weight $\kappa_{1\%,AB}$, which is positive and statistically significant at the 1% level. Columns (2)-(4) contain the results for the GGL measures that assume full attention, a fitted, and a concave attention function, respectively. These coefficients also are positive and significant at the 1% level. Then Columns (5) and (6) indicate that the coefficients of $GGL_{\text{linear}}$ and $GGL_{\text{convex}}$ are positive and significant at the 5% level.

[Table 5 about here.]

In all six regressions, the technological distance coefficient is negative and significant at the 1% level. As expected, a firm is more likely to buy a given technology if it is more proximal to its existing patent stock in the technology space, because these reassigned patents contribute more to firm value in this case (Akcigit, Celik and Greenwood, 2016). In addition, more innovative firms appear more likely to buy a technology, according to the coefficient of *Pstock* (i.e., average number of patents produced in the previous 5 years), which is significant at the 1% level. In contrast, assignees' short-term innovation intensity, measured by R&D expenditures normalized by total assets, has no significant association with patent reassignments.

The indicator for board connections is significant only in Columns (1) and (6) but positive in all regressions, with $p$-values below 0.2. Thus, common directors may play some role in matching firms in the market for technology. A potential relationship between common ownership and interlocking directorates also has been noted in recent research (Azar, 2022), particularly in antitrust studies that address the potential anticompetitive effects of both phenomena (Nili, 2019, 2022; Fletcher, Peitz and Thépot, 2022).[20] However, common directors between firms that engage with others as technology providers and potential adopters could influence the gains obtained from the trade and the matching in the market for ideas. Therefore, I discuss the interaction of executive common directors with common ownership in Section 7. At this point, my focus is on the effect of common ownership, beyond that induced by the presence of common directors on two boards.

[Table 6 about here.]

Table 6 contains probit regressions, in which I exclude all dyads with common directors (that is, observations for which the indicator variable $CD_{AB,tj}$ takes a value of 1), as well as all deal groups (i.e., the entire set of actual and counterfactual dyadic observations for a given reassignment) in which the assignor transfers the patent bundle to a firm with which it shares a director. Keeping only observations for which $CD_{AB,tj}$ equals 0 and re-estimating Equation (8) without the board connection indicator yields qualitatively similar results to those in Table 5. In detail, Column (1) of Table 6 reveals the coefficient for the profit weight measure of common ownership, which again is positive and significant at the 1% level. The coefficients of the other measures of common ownership also are very similar for the sample without board connections. The coefficient of $GGL_{\text{convex}}$ becomes significant at the 1% level and increases somewhat in magnitude.

[20] See also the special issue on "Common Ownership and Interlocking Directorates" in the *Journal of Competition Law and Economics*.

*Instrumental Variable Model.*—Table 7 contains the first-stage regressions for the IV estimation. For all measures of common ownership, the coefficient of the instrument is highly significant, confirming that it is relevant, and the F-statistics are all comfortably above the critical values, alleviating concerns about potentially weak identification. Thus, ownership in potential adopters of those investors that are pure index trackers of the indexes the assignor belongs to has strong explanatory power for the strength of common ownership linkages as measured by the profit weight and GGL measures.

[Table 7 about here.]

Table 8 provides the causal effects of common ownership on matching assignees to technology providers. The coefficient of the profit weight (Column 1) is positive and significant at the 5% level; the coefficients of the GGL measures (Columns 2-6) are all positive and significant at the 1% level. Thus, these results are quantitatively and qualitatively very close to those obtained from the probit regression model.

[Table 8 about here.]

*Quantitative Assessment.*—To gauge the economic significance of the impact of common ownership between technology providers and potential adopters, I next calculate the marginal effects of a one standard deviation increase of common ownership, relative to the sample mean, on the probability that a firm becomes an assignee of a specific technology. The unconditional probability in the IV sample is approximately 1.06%.[21] The marginal effect of the profit weight $\kappa_{1\%,AB}$ corresponding to the coefficient in Column (1) of Table 8 is 0.017, and the standard deviation of the measure in the sample is 0.526. Thus, the percentage increase in the unconditional probability resulting from an increase in $\kappa_{1\%,AB}$ by one standard deviation is $(0.017 \times 0.526)/0.0106 \approx 92.54\%$. The marginal effects of the GGL measures are greater; they range from 174% for the fitted attention function (which is concave and closely correlated with the full attention version) to 268% if I assume a convex relationship between portfolio weights and investor attention with respect to the technology provider.

I have constructed matched samples. Using the Mahalanobis distance for example, I derived a sample with exactly four counterfactual pairs matched to one actual trading pair, such that the unconditional probability of reassignment is 0.2 for each deal group.[22] In this sample, the marginal effects are naturally lower, due to the higher unconditional probability. However, they remain sizeable. For example, for the profit weight $\kappa_{1\%,AB}$, a one standard deviation increase relative to the mean increases the probability of reassignment from 20% to greater than 30%, which corresponds to a marginal effect in excess of 50%. The greater effects of the GGL measure then range from 76% for the full attention measure to 231% for the linear version.

From these calculations, I derive another insight as well. Recall that the GGL measures can be interpreted as managerial incentives, induced by common ownership (because they were derived from an agency problem) and reflect different assumptions about monitoring activity by

[21] There are 155 technology transfers among the sample of 14,620 observations.

[22] In Section 1 of the Online Appendix, Table 3 contains summary statistics for this sample, and Table 4 offers the corresponding regressions.

institutional investors. Here, they represent the incentives that drive the managers of technology providers to internalize the effects of the reassignment on adopters' profit. According to the marginal effects, the probability that partners engage in a transfer doubles when assuming full attention; it more than triples if the differences in the amount of attention investors pay to assignors' management are strongly reflected by the common measures, as is the case for the linear or convex versions of GGL. Because the latter two measures display greater effects, it is possible to infer that in the case of technology transfers, it is more important for a firm to appear in the upper ranks of the investor's portfolio (i.e., high portfolio weight) for the investor to monitor such activity compared to voting on simple corporate governance issues, from which $GGL_{\text{Fitted},AB}$ has been created by Gilje, Gormley and Levit (2020).

To explain these results, I provide a theory in the next section from which further testable hypotheses are derived. This analysis and further empirical tests allow me to identify the mechanism by which common ownership affects the reallocation of technologies.

# 4 A Model of the Market for Technology with Common Ownership

I present and analyze a simple model of the market for technology and the implications of common ownership between a technology provider, firm $A$, and potential adopters, firms $B_l$, $l = 1, 2, 3, \ldots, n$. In this assessment, firm $A$ is the initial owner of the technology. It does not benefit from applying the technology itself, perhaps because the field of application is distant from its core line of business (Akcigit, Celik and Greenwood, 2016) or because it lacks necessary, complementary assets, to which access is restricted (Teece, 1986; Arora and Ceccagnoli, 2006). In contrast, firms $B_l$ are potential adopters of the technology codified in firm $A$'s patents and would benefit from obtaining exclusive rights to it, though to varying degrees.

Let $\pi_{B_l}$ be the operational profits of firm $B_l$. Then the ex ante operational profits of firm $B_l$ can be denoted by $\tilde{\pi}_{B_l}$, representing the profits of firm $B_l$ if it does not adopt the technology. If firm $B_l$ becomes the assignee and adopts the technology, it earns higher operational profits $\pi^r_{B_l}$, such that $\pi^r_{B_l} > \tilde{\pi}_{B_l}$. But if its rival in the market for technology buys the patents, firm $B_l$ continues to operate with its old technology and earns profits equal to $\tilde{\pi}_{B_l}$. In this case, no business stealing effects arise between the potential adopters, such that the adoption of the technology by one potential assignee does not hurt the other.[23]

The extent to which the potential adopters benefit from applying the technology is heterogeneous, depending on firm characteristics such as absorptive capacity, innovativeness, growth potential, and financial frictions. The technological propinquity between the reassigned technology and the firm's location in the technology space also affects adopters' ability to profit from the reassignment. Thus, $\Delta\pi_{B_l} \equiv \pi^r_{B_l} - \tilde{\pi}_{B_l}$ is firm-specific.

I assume no product market rivalry exists between the assignor and the potential assignees either. Thus, the operating profits of the assignor, earned through its core business activities, are

[23] Hutschenreiter (2022) provides a model that includes business stealing effects among adopters.

unaffected by the transfer of technology and can be ignored in the model.[24] This assumption simplifies the analysis and helps reveal the direct impact of common ownership on assignee selection. I also normalize firm $A$'s operational profits to 0.

A technology transfer contract reassigns intellectual property rights to the technology, from the assignor (firm $A$) to the assignee (some firm $B_l$). It also stipulates a fixed fee payment $F \geq 0$ from the assignee to firm $A$. I do not consider contracts with royalty payments; in the market for technology, lump-sum payments for the provision of intellectual property rights appear more common (see also Arqué-Castells and Spulber, 2021).[25] Moreover, they are efficient under symmetric information, and in the absence of product market rivalry among the partners; a fixed fee does not distort an adopter's product market strategy. All the qualitative results also hold even when I allow for the possibility of royalties.[26] Finally, if firm $A$ reassigns the technology to firm $B_l$, it incurs a cost of technology transfer, $C \geq 0$.

Having described the contract $F$, the cost of the technology transfer $C$, and the operational profits of the potential adopters $\pi_{B_l}$, I can define firms' net profit functions. Firm $A$'s net profits when it reassigns the technology to firm $B_l$ equal the difference between the fixed payment and the cost of the technology transfer, $\mathit{\Pi}_A = F - C$ (recall that the operating profits are normalized to 0).

Potential adopters earn net profits denoted by $\mathit{\Pi}_{B_l}$ for $l = 1, 2, \ldots, n$. If firm $A$ keeps the technology, firm $B_l$'s net profits coincide with its ex ante operational profits, and $\mathit{\Pi}_{B_l} = \tilde{\pi}_{B_l}$. If, however, one of the potential adopters, say firm $B_1$, makes a deal with firm $A$, it earns net profits of $\mathit{\Pi}_1 = \pi_1^r - F$, while the other potential assignees earn net profits of $\mathit{\Pi}_{B_l} = \tilde{\pi}_{B_l}$ for all $l \neq 1$.

Before solving the model, I describe how common ownership likely influences a manager's decisions.

## 4.1 Common Ownership Incentives

In industrial economics in general, and research into technology transfers in particular, a standard assumption is that the profit function of a firm is equivalent to the objective function of the agents that make decisions on behalf of the firm and thereby establish the firm's strategy. In such

[24]For an analysis of the effect of product market interactions between providers and adopters of technology, see Arqué-Castells and Spulber (2021).

[25]In a study of patent assertion entities, the FTC (Federal Trade Commission, 2016) collected confidential business information about licensing contracts by executing its authority under Section 6(b) of the Federal Trade Commission Act. The findings indicate that 83.7% of licensing contracts only include lump-sum payments, 13.5% include only running royalties, and just 2.8% of contracts rely on both fixed and royalty payments. For patent reassignments, the use of lump-sum payments appears even more pervasive. Furthermore, among a sample of Spanish technology adopters, Macho-Stadler, Martinez-Giralt and Pérez-Castrillo (1996) find that if a technology transfer involves property rights, a greater share of contracts features fixed fee payments, compared with deals that involve only the transfer of use or commercial rights. Variable royalty payments, based on the use of the technology or sales by the assignee that stem from the application of the patents, require permanent monitoring by the assignor, which is very costly.

[26]Royalties introduce an inefficiency if the operational profits depend on the amount of the royalty. Imagine two potential assignees are monopolists in their respective product markets, facing a downward-sloping demand function. In that case, a royalty payment based on the produced quantities increases the technology adopter's effective marginal costs, thereby reducing the value of the technology transfer.

models, firms act as profit maximizers, reflecting the assumption that firm owners want to and can incentivize managers to work in their best interests, namely, by maximizing profits.

However, the common ownership hypothesis instead states that investors that hold shares in various firms seek to maximize the value of their portfolio, so they promote managerial incentives and firm behavior that potentially depart from exclusively profit maximization goals (Schmalz, 2018; Backus, Conlon and Sinkinson, 2020). Rather than behaving as independent profit maximizers, firms function as if they are parts of a larger corporate structure.

Azar (2017) and Gilje, Gormley and Levit (2020) propose different models of how common owners can induce managers to internalize their preferences through voting in annual meetings. Antón et al. (2021*a*) also show that common ownership affects the monetary incentives provided in compensation contracts to managers.

The model proposed herein abstracts away from the concrete mechanism that leads managers to consider common owners' preferences. Ultimately, it is reasonable to anticipate that institutional investors that monitor managers' behavior also can influence their decision-making, especially if they have access to the managers during informal meetings or through shareholder representation. Institutional investors also might influence portfolio firms' management through active engagement.[27] Diversified investors, such as index funds that frequently function as common owners, seem to engage closely with portfolio firms' management teams. As described by Shekita (2022) for example, BlackRock engaged with thousands of companies, often multiple times, in 2019.

Whereas common owners thus appear to want to influence managerial decisions, managers may be reluctant to internalize those common owners' preferences. Azar (2017) points out that shareholder voting to contest management teams is costly, and Conyon (2015) finds that shareholder votes against management in "say-on-pay" proposals reduce CEO pay. Aggarwal, Dahiya and Prabhala (2019) reveal that voting against directors in uncontested elections makes those directors more likely to leave the board or, if they stay, take less prominent positions. Such directors also encounter reduced opportunities in the market for directors. Given investors' direct engagement with management, strong evidence exists of common owners' ability to influence managerial decisions. Managers may anticipate consequences if they do not follow recommendations or requests from investors; they also may engage strategically in gift exchanges or positive reciprocity with investors in their efforts to build up their reputations as reliable partners (Akerlof and Yellen, 1990; Fehr and Gächter, 2000). When common owners are very diversified, they likely can influence management even more, by virtue of their presence in many companies and industries, such that

[27] According to Glenn Booraem, Principal and Fund Controller at Vanguard Fund Financial Services, "As major and practically permanent holders of most companies by virtue of our significant index franchise, we have a vested interest in ensuring that governance and compensation practices support the creation of long-term value for investors—a key to achieving investment success.... This is where the second—and perhaps more important—component of our governance program takes over; engagement with directors and management of the companies in which we invest provides for a level of nuance and precision that voting, in and of itself, lacks. So while voting is visible, it tells only part of the story.... We believe that engagement is where the action is. We have found through hundreds of direct discussions every year that we are frequently able to accomplish as much—or more—through dialogue as we are through voting.... We believe that our independent analysis, supported by substantive engagement, puts us in the best position to both vote on an informed basis and influence corporate behavior appropriately" (Booraem, 2013).

they could influence managers' and directors' future career prospects in other firms.[28]

In line with previous literature, I model the incentives induced by common ownership in a reduced form. For simplicity, assume that managers internalize shareholders' preferences, and the degree of internalization depends on the extent of overlapping ownership. That is, assume a set of investors $i = 1, 2, \ldots, I$. Each investor can hold shares in several companies. Similar to Rotemberg (1984), Azar (2017), and López and Vives (2019),[29] I assume that firm $A$'s management maximizes the weighted average of its shareholders' wealth. According to López and Vives (2019), this assumption leads to the following objective function[30]

$$\phi_A = \mathit{\Pi}_A + \sum_l \lambda_{AB_l} \mathit{\Pi}_{B_l}, \tag{11}$$

where $\lambda_{AB_l}$ is the profit weight that the management of firm $A$ assigns to the profits of firm $B_l$ in its objective function. Therefore, firm $A$ behaves as if it would maximize a weighted sum of its own and other firms' profits.

The connection between the theoretical profit weight $\lambda_{AB_l}$ and the empirical profit weight $\kappa_{1\%,AB}$ in the empirical analysis is evident.[31] Alternatively, I could model managerial incentives in the manner Gilje, Gormley and Levit (2020) do, but doing so would produce a similar objective function. Therefore, I interpret $\lambda_{AB_l}$ as any measure that gauges the incentives of firm $A$'s management, resulting from common ownership, which also may encompass the degree to which investors pay attention to firm $A$'s management.

## 4.2 Technology Transfer under Common Ownership and Symmetric Information

To study the effect of common ownership on the matching in the market for technology, I analyze a simple version of the assignment game introduced by Shapley and Shubik (1972). An appealing

[28] Aghion, Van Reenen and Zingales (2013) show that institutional investors influence managerial decisions about investing in innovation by affecting career concerns.

[29] López and Vives (2019) also discuss how different arrangements of overlapping ownership structures may influence the way firms internalize the profits of rivals. See also O'Brien and Salop (2000).

[30] This objective function can be derived easily: Let the share held by investor $i$ in company $j \in \{A, B_1, B_2, \ldots, B_n\}$ be denoted $\beta_{ij} \in [0, 1]$, with $\sum_i \beta_{ij} = 1$. Let investor $i$'s wealth be given by $W_i = \sum_j \beta_{ij} \mathit{\Pi}_j$, $i = 1, \ldots, I$. If the manager of firm $A$ maximizes a weighted sum of investors' wealth,

$$\sum_i \gamma_{iA} W_i,$$

where $\gamma_{iA}$ are Pareto weights that the manager of firm $A$ assigns to investor $i$, then the maximization problem yields the same solution as Equation (11), in which $\lambda_{AB_l} \equiv (\sum_i \gamma_{iA}\beta_{iB_l})/(\sum_i \gamma_{iA}\beta_{iA})$, $l = 1, 2, \ldots, n$. The Appendix (Section A.1) provides a more detailed derivation.

[31] The empirical profit weight, $\kappa_{1\%,AB}$, is not restricted to the interval $[0, 1)$. However, I interpret this measure as an ordinal measure of common ownership incentives. It is reasonable to assume that managers always weight their own firm's profits more than other firms' profits, as long as managerial decision-making is not fully dominated by common owners. Thus, in the theoretical model, I assume that the common ownership incentives internalized by firm $A$'s management equal $\lambda_{AB_l} \in [0, 1)$.

feature of this framework is that the bargaining power of two partners interacting in a market is endogenously determined through the presents of other potential partnerships.

A *matching* in the market for ideas is a function $\mu$, such that $\mu(B_l) \in \{A, B_l\}$, and $\mu(A) \in \{A, B_1, B_2, \ldots, B_n\}$. Either potential assignee, such as $B_l$, might be matched to firm $A$, so $\mu(A) = B_l$, and $\mu(B_l) = A$, and then adopt the technology. Other firms, such as $B_{l'}$, remain unmatched ($\mu(B_{l'}) = B_{l'}$, for $B_{l'} \neq B_l$). Alternatively, firm $A$ might keep the technology ($\mu(A) = A$ and $\mu(B_l) = B_l$ for all $B_l \in \{B_1, B_2, \ldots, B_n\}$).

An *outcome* is a tuple $(\mu, F)$, such that it includes the matching $\mu$ and a fixed fee $F \geq 0$ paid by firm $\mu(A)$ to firm $A$. Furthermore, an outcome of the game is stable if two conditions are satisfied. First, it must be individually rational:

$$\phi_A(\mu(A), F) \geq \tilde{\phi}_A, \tag{12}$$

$$\mathit{\Pi}_{\mu(A)}(A, F) \geq \tilde{\pi}_{\mu(A)}, \tag{13}$$

where $\tilde{\phi}_A$ and $\tilde{\pi}_{\mu(A)}$ are the outside options of firms $A$ and $\mu(A)$,[32] respectively, of staying unmatched. Second, there does not exist any blocking pair, such that for some $B_l \neq \mu(A)$ and any fixed fee $F' \geq 0$

$$\mathit{\Pi}_{B_l}(A, F') > \tilde{\pi}_{B_l} \quad \text{and} \tag{14}$$

$$\phi_A(B_l, F') > \phi_A(\mu(A), F). \tag{15}$$

Let $F^o_{B_l}$ denote the fee that makes a potential adopter $B_l$ indifferent between buying or not buying the technology. In that case, $F^o_{B_l}$ is defined by

$$\mathit{\Pi}_{B_l}(A, F^o_{B_l}) = \tilde{\pi}_{B_l}. \tag{16}$$

A blocking pair does not exist if and only if for any $B_l$

$$\phi_A(\mu(A), F) \geq \phi_A(B_l, F^o_{B_l}). \tag{17}$$

Recall that $\mathit{\Delta}\pi_{B_l} \equiv \pi^r_{B_l} - \tilde{\pi}_{B_l}$ is the increase in operating profits of any firm $B_l$ when becoming the adopter. Since the adopter's financial profits decrease with the fixed fee,[33] from Equation (17) it follows that firm $A$ prefers to reassign the technology to firm $\mu(A)$ if and only if

$$F \geq \frac{1}{1 - \lambda_{A\mu(A)}}(\mathit{\Delta}\pi_{B_l} - \lambda_{A\mu(A)}\mathit{\Delta}\pi_{\mu(A)}), \tag{18}$$

[32]The outside option of firm $A$ is $\tilde{\phi}_A \equiv \sum_{\mathcal{B}} \lambda_{AB_l}\tilde{\pi}_{B_l}$, where $\mathcal{B} \equiv \{B_l | l = 1, 2, \ldots, n\}$, because the operational profits of firm $A$ have been normalized to 0.

[33]It is possible to rewrite Equation (12) as

$$F \geq \frac{C - \lambda_{A\mu(A)}\mathit{\Delta}\pi_{\mu(A)}}{1 - \lambda_{A\mu(A)}}.$$

Because the empirical analysis only includes technologies that have been reassigned to some adopter, I assume that this condition is always satisfied.

because by Equation (16) $F^o_{B_l} = \Delta\pi_{B_l}$ must hold.

According to Equation (13), firm $\mu(A)$ finds it profitable to adopt the technology at a fixed fee $F$ if and only if

$$F \leq \Delta\pi_{\mu(A)}. \tag{19}$$

Therefore, by combining Equations (18) and (19), a necessary condition for $F$ to exist and for $(\mu, F)$ to be a stable outcome emerges:

$$\Delta\pi_{\mu(A)} \geq \Delta\pi_{B_l}, \quad \text{for all } B_l,\ l = 1, 2, \ldots, n. \tag{20}$$

Only the firm that profits most from the technology can become the adopter in equilibrium. Equivalently, it is possible to express Equation (20) in terms of the surplus of the match, by subtracting the transfer costs $C$ from both sides. I summarize this result in the following lemma.

**Lemma 1.** *If a technology transfer occurs in the market for technology under common ownership and symmetric information, the technology gets transferred to the firm that benefits the most from adopting it, and the matching generates the highest possible surplus.*

The following proposition follows immediately from this lemma.

**Proposition 1.** *Under symmetric information, the matching in the market for technology is independent of common ownership.*

Thus, under symmetric information, common ownership does not influence the matching in the market for technology. Therefore, there must exists some information or agency friction in the market for technology that causes common ownership to have an effect on technology reallocation, as shown in Section 3. In the next subsection, I propose an extension of the model in which a part of the technology transfer is unverifiable and show that this moral hazard problem can explain the effect of common ownership found in the data.

## 4.3 Technology Transfer under Common Ownership and Moral Hazard

In this section, I study environments in which the technology transfer is not fully verifiable. For example, a technology transfer might consist of both trading intellectual property rights and transferring innovative know-how. The latter facilitates the application of the technology, so it benefits the adopter. Know-how generally is not fully revealed in patents, such that it constitutes private knowledge of the inventing firm and has to be transferred, e.g., by means of technical services, such as the training of personnel, trips by the engineers of the assignor and other services offered by the technology provider (Teece, 1977; Arora, 1995). Indeed, technology transfers are often composed of information, rights, and such technical services, which are the means by which know-how is transferred (Contractor and Sagafi-Nejad, 1981). Ensuring that the buyer gains the full benefits of adoption requires the seller of the technology to transfer this uncodified know-how, which requires incentives to do so (Macho-Stadler, Martinez-Giralt and Pérez-Castrillo, 1996).

In the model, the technology provider, firm A, transfers a patent or bundle of patents. It also can transfer an unverifiable component of the technology in the form of know-how. This know-how transfer is subject to moral hazard because the know-how itself is not codified in the patents. Thus, its transmission is a separate and costly action.

Let the amount of unverifiable know-how transferred be denoted by $k_{B_l} \geq 0$. Considering that this know-how seemingly should increase the profitability of adopting the technology, $\pi^r_{B_l}$ becomes a function of $k_{B_l}$. If I denote $\Delta_{B_l}$ as the increase in firm $B_l$'s profits if $k_{B_l} = 0$, then $\Delta_{B_l}$ measures how much firm $B_l$ can benefit from adopting the technology without know-how transfers. In this sense, $\Delta_{B_l}$ corresponds to the firm characteristics or technological propinquity of a potential assignee in the empirical analysis. To complete the description of this model with moral hazard, I also make two assumptions.

**Assumption 1.** *If firm $A$ reassigns technology to firm $B_l$, the ex post profit of firm $B_l$ increases linearly with know-how transfer, such that*[34]

$$\pi^r_{B_l} = \tilde{\pi}_{B_l} + \Delta_{B_l} + \gamma k_{B_l},$$

*and* $\gamma > 0$.

**Assumption 2.** *If firm $A$ transfers an amount $k_{B_l}$ of know-how, it incurs a cost of* $C(k_{B_l}) = \frac{1}{2}k^2_{B_l}$.

Timing considerations also are needed to incorporate moral hazard into the assignment game. At stage 1, the matching $\mu$ is determined, and if a firm $B_l$ matches with the technology provider firm $A$, they enter into the fixed-fee contract $F$. In this case, in stage 2 the management of firm $A$ chooses the amount of know-how $k_{B_l}$ and transfers it to the matched firm.

Applying backward induction, suppose that in the first stage, an outcome $(\mu, F)$ has occurred, and $\mu(A) \neq A$. Thus, firm $A$ and some firm $\mu(A)$ have signed contract $F$, and the ownership of intellectual property rights has been reassigned. Firm $A$'s manager then determines the amount $k_{\mu(A)}$ to be transferred. The manager chooses the amount such that it maximizes the objective function under common ownership. Therefore, the incentive-compatible know-how transfer reflects

$$k_{\mu(A)} = \arg\max_{\hat{k}_{\mu(A)}} F + \lambda_{A\mu(A)} \Big[(\Delta_{\mu(A)} + \gamma \hat{k}_{\mu(A)}) - F\Big] - \frac{1}{2}\hat{k}^2_{\mu(A)}. \tag{21}$$

This incentive compatibility constraint indicates that, independent of the fixed fee $F$, firm $A$ credibly transfers to firm $\mu(A)$ the amount of know-how,

$$k_{\mu(A)} = \gamma \lambda_{A\mu(A)}. \tag{22}$$

Thus, Equation (22) indicates that the know-how transfer is a function of common ownership between the technology provider and the adopter. Moreover, the derivative $\partial k_{\mu(A)}/\partial \lambda_{A\mu(A)} = \gamma$ is positive, because $\gamma > 0$. The following lemma thus emerges:

**Lemma 2.** *The greater the incentives for managers of the assignor to internalize the adopter's profit, the more unverifiable know-how that gets transferred.*

[34] Considering that $k_{B_l}$ is not verifiable, I could also assume that $\pi^r_{B_l} = \tilde{\pi}_{B_l} + \Delta_{B_l} + \gamma k_{B_l} + \epsilon_{B_l}$, where $\epsilon_{B_l} \sim \mathcal{N}(0, \sigma^2_{B_l})$, such that $k_{B_l}$ cannot be inferred from the assignee's profit. Since universal risk-neutrality prevails, adding noise does not change the analysis.

Having solved for the know-how transfer at stage 2, in the first stage I seek to identify the conditions in which $(\mu, F)$ is a stable outcome. Anticipating the know-how transfer, according to Equation (19), firm $\mu(A)$ finds it profitable to adopt the technology if and only if

$$F \leq \Delta\pi_{\mu(A)}(k_{\mu(A)}) = \Delta_{\mu(A)} + \gamma^2\lambda_{A\mu(A)}. \tag{23}$$

Similarly, I can derive $F^o_{B_l}$, the highest fixed-fee an alternative adopter would be willing to pay when matched with the provider:

$$F^o_{B_l} = \Delta\pi_{B_l}(k_{B_l}) = \Delta_{B_l} + \gamma^2\lambda_{AB_l}. \tag{24}$$

If I define $\Lambda_{AB_l} \equiv \lambda_{AB_l}(1 - \frac{1}{2}\lambda_{AB_l})$, then for all $\lambda_{AB_l} \in [0, 1)$, $\Lambda_{AB_l}$ is strictly increasing in $\lambda_{AB_l}$. Using Equations (17) and (24) and Assumptions 1 and 2, and given that a technology transfer takes place, $(\mu, F)$ is a stable outcome if and only if

$$[\Delta_{\mu(A)} - \Delta_{B_l}] + \gamma^2\left(\Lambda_{A\mu(A)} - \Lambda_{AB_l}\right) \geq 0, \quad \text{for all } B_l,\ l = 1, 2, \ldots, n. \tag{25}$$

From Inequality (25) follows the next proposition:

**Proposition 2.** *In the market for technology under common ownership and moral hazard in know-how transfer*

1. *it is more likely that a firm $B_l$ adopts the technology if common ownership $\lambda_{AB_l}$ (and, thus, $\Lambda_{AB_l}$) increases,*
2. *the effect of an increase in $\lambda_{AB_l}$ on the likelihood that the firm $B_l$ becomes the assignee is stronger if the productivity of unverifiable know-how $\gamma$ is larger.*

## 4.4 Model Discussion and Hypotheses Development

In Section 4.2, I established that common ownership between the assignor and potential assignees does not affect the selection of the actual assignee under symmetric information (Proposition 1). In this model, it does not matter whether the manager of the technology provider takes into account the preferences of common owners.

Then in Section 4.3, I showed that moral hazard related to know-how transfers leads to a positive effect of common ownership on the selection of a potential adopter (Proposition 2). This effect stems from the improved quality of the technology transfer, which in turn increases the surplus of a match for a potential adopter with which the provider shares more common ownership. The management of the adopter anticipates the know-how transfer, so it exhibits a higher willingness to pay (a higher fixed fee) than alternative adopters.[35] In this sense, moral hazard in know-how transfer provides a possible explanation for the effect of common ownership on the matching of firms in the market for technology.

[35] This point is more crucial than the assumption that managers of the provider account for the preferences of common shareholders during the contracting stage, as long as ex post, after signing the contract, common shareholders can enforce incentive-compatible know-how transfers.

The baseline results presented in Section 3 show that common ownership has a significant effect on the probability that a potential adopter gets selected. Thus, the model of the market for technology with transfers of unverifiable know-how (moral hazard) is consistent with the empirical results. However, moral hazard might not be the only reason common ownership affects the matching. Here, however, I first develop some further hypotheses based on the moral hazard model, which I test in Section 5. Furthermore, I consider matching frictions as an alternative explanation in Section 6.

Proposition 2 indicates that the impact of common ownership is stronger if the productivity of the unverifiable know-how transfer is greater (i.e., a higher $\gamma$). In other words, for technologies for which all necessary know-how is either codified in patents or available in the public domain, the effect of common ownership on the reallocation of the patents should be attenuated. Conversely, for technologies for which this know-how can only be obtained from the innovator or technology provider, the effect of common ownership is stronger. The transfer of know-how by the provider in this latter scenario affects the profits of the adopter more substantially, with relevant effects on the matching in the market.

Technologies differ in the extent to which their application also requires specialized, uncodified know-how, shared by their initial owners. Simpler, older technologies may not require any such know-how transfers, but complex and new technologies often demand substantial such transfers before the acquirer can fully exploit them in productive ways (Macho-Stadler, Martinez-Giralt and Pérez-Castrillo, 1996). In particular, complex innovations often combine know-how from various technological areas, which increases the cost of adoption without the help of the innovator (Teece, 1977).[36] If such know-how is not codified in the individual patents of the bundle that comprises the intellectual property linked to this technology, the assignee cannot reasonably access it and needs to receive know-how from the technology provider. Thus, the positive effect of common ownership on assignee selection may be stronger for complex technologies, new technologies, or recent innovations that have not been widely applied or exploited outside the innovating firm. In the scenario of recent innovation being reassigned, little complementary know-how has accrued among researchers or employees outside the innovating firm, so the transfer of uncodified know-how becomes even more crucial for an efficient adoption of the technology by the assignee. Formally,

**Hypothesis 2.** *The effect of common ownership on assignee selection is more substantial if the reassigned technology represents a recent or more complex innovation.*

The moral hazard model also predicts that, conditional on a technology transfer taking place, the amount of know-how transferred and the quality of the transfer both increase with common ownership. Such considerations also affect the degree to which the adopter can benefit from the technology adoption. The unverifiable know-how is valuable for integrating the technology into the adopters' knowledge capital, so better quality technology transfers should increase adopters' future innovativeness. To determine if a technology transfer leads to better results if common ownership is higher, I test the following hypothesis:

[36] Contractor and Sagafi-Nejad (1981) also present evidence that transnational technology transfers of more complex technologies more frequently involve foreign direct investments or equity arrangements to secure a higher quality transfer. These arrangements analogously provide incentives for the transmission of unverifiable know-how, albeit in a more direct manner than common ownership by institutional investors.

**Hypothesis 3.** *A technology transfer increases the number of future patents and citations by a technology adopter to a greater extent if there is more common ownership between the technology provider and adopter.*

Finally, common ownership and the transfer of uncodified know-how affect the value of adopting the technology. This outcome is the primary reason common owners are interested in the quality of the know-how transfer. To study this effect, I hypothesize:

**Hypothesis 4.** *A technology transfer increases the future market capitalization growth of a technology adopter more if the common ownership incentives for the provider's managers are higher.*

# 5 Testing the Model

Having established the significant positive effect of common ownership on the probability that a potential assignee becomes the adopter of the technology (Hypothesis 1) in Section 3, in this section, I address further implications of the model discussed in the previous subsection.

*Recent Innovations.*—The test of Hypothesis 2 relies on the heterogeneity of the technologies reassigned in the sample. With the application dates of reassigned patents and the execution date of the ownership transfer, I compute the age of individual patents in each bundle, then weight the individual age of a patent by its citations, correcting for truncation (Hall, Jaffe and Trajtenberg, 2001; Atanassov, 2013), to obtain the age of each reassigned technology, i.e.,

$$a_r = \sum_{p \in \mathcal{R}} a_p w_p, \tag{26}$$

where $a_p$ is the age of an individual patent in the bundle, and $w_p$ is the weight of each patent, equivalent to the number of citations the patent received up until 2010, scaled by the average number of citations of patents in the same application year and technology class, divided by the sum of this statistic for all patents $p \in \mathcal{R}$, with $\sum_{p \in \mathcal{R}} w_p = 1$.

Then with an indicator variable, $recent_r$, I identify those technologies with an average age below the median of the sample. As I have argued, the moral hazard problem for know-how transfers should be more severe if the technology is younger. Thus, common ownership should be more relevant and exert a stronger effect on the reallocation of recent innovations compared to older ones. To test this prediction, I run the baseline IV regression, adding an interaction term of common ownership with the indicator $recent_r$, as well as the indicator itself, as regressors. As the results in Table 9 reveal, the interaction term is positive and significant at the 1% level (Columns 1-5). In Column (6), which refers to the convex version of the GGL measure, the interaction term is positive, but the $p$-value is 0.228.

Overall, I find significantly different and stronger effects of common ownership on the reassignments involving recent innovations. The effect for older technologies instead is insignificant or slightly negative (Column 1). This result is consistent with Hypothesis 2 and the model in which common ownership alleviates the moral hazard problem for know-how transfers.[37]

[37] Estimating a simple probit model gives qualitatively similar results. The interaction term of $recent_r$ and the profit weight is positive and significant at the 5% level. The interaction terms based on the GGL measures are all positive and significant at the 1% level.

[Table 9 about here.]

To gauge technological complexity, I use an inverse measure of the concentration of the patent bundles in 2-digit SIC patent classes.[38] The $complexity_r$ measure and its interaction with common ownership measures appear in the baseline probit model. The results in Table 16 in the Appendix confirm Hypothesis 2, such that they reveal a positive interaction of common ownership and $complexity_r$. This finding holds for regressions that include the profit weight (Column 1), as well as the concave, linear, and convex versions of GGL (Columns 4-6) as measures of common ownership. The latter three measures overweight investors that likely devote more monitoring effort to the assignors' management, which is consistent with the idea that the presence of these common owners induces incentives for providers' management that alleviate moral hazard in the transfer of know-how.

*Future Innovations.*—As mentioned, the moral hazard model predicts increased technology transfer qualities if the common ownership incentives of the technology provider with respect to the adopter are greater. Thus, we expect that an adopter can exploit ideas codified in the patents better in the presence of more common ownership. To test if common ownership leads to more future patents and citations, I construct a dyadic panel, using observations for the whole sample period (1990-2006) and the same pairs of assignors and potential assignees that appeared in the baseline analysis.[39] Accordingly, I can control for dyad- and time-specific unobservables by including year and firm-pair fixed effects.

[Table 10 about here.]

Table 10 presents the effects of reassignment and common ownership on adopters' patents (*LnPatent*) and citations (*LnCitation*) in year $t$, estimated with an ordinary least squares model. Here, I expect a positive interaction of common ownership measures with the dummy variable $Reass_{AB,r}$, because more common ownership should lead to more innovations by the adopter, conditional on a reassignment taking place. According to Column (1), neither the indicator variable $Reass_{AB,r}$ nor the profit weight $\kappa_{1\%,AB}$ (or their interaction) produces a coefficient significantly different from 0 in the regression for patent output. A similar finding emerges for citations (Column 2).

The broader pattern reveals a more interesting picture: When common ownership measures account for institutions' likelihood to pay attention to providers' managerial decisions, the interaction term becomes positive and significant, at the 5% level in Columns (7) and (8) for the concave version and at the 1% level in Columns (9)-(12) for the linear and convex version of GGL. Yet the differences in the measures do not reflect adopters' characteristics but rather the characteristics of providers relative to institutional investors. That is the providers' weight in the investors' portfolios. This relationship seems to capture, as predicted by Gilje, Gormley and Levit (2020), how much attention investors pay to the managerial decisions of portfolio firms (here of the technology providers) and, in turn, how much the managers take care of responding to this attention

[38] See Hutschenreiter (2022) and Table 1 for more details.

[39] For example, if two firms transfer technology in 2000, I include a dyadic observation of this pair and counterfactual pairs for the whole sample period, as long as both firms are active and data on firm characteristics and common ownership are available.

by internalizing these investors' preferences. Recall also that these measures had a quantitatively stronger effect on technology reallocation, as shown in Section 3.

Furthermore, I find similar patterns for patents and citations in $t+1$ and $t+2$, that is, one and two years after the reassignment. Table 11 contains the results for the linear and the convex versions of GGL. In Columns (1)-(4), the results for future patents and citations are based on $GGL_{\text{Linear},AB}$ and its interaction with $Reass_{AB,r}$. All the interaction terms are positive and significant. This result also holds if I use $GGL_{\text{Convex},AB}$, as in Columns (5)-(8). Finally, using the IV strategy to instrument $GGL_{\text{Linear},AB}$ and the interaction term, as in Columns (9)-(12), the coefficients of the interaction term again are positive and significant at the 1% level.

[Table 11 about here.]

*Future Market Cap Growth.*—Common owners engage with managers to achieve a more efficient technology transfer, because they are motivated to increase the financial success of their stock market investments in those firms. Mutual and index funds usually earn fees as a percentage of assets under management. In addition to fund inflows, their earnings can also increase when the value of the assets increases, such as when the stock market value of the companies rises.

[Table 12 about here.]

In Table 12, using the same dyadic panel, I estimate the effect of common ownership on the future market capitalization growth of the potential assignees one year after the reassignment. Here, the focus is on the effect of common ownership, conditional on a reassignment taking place, so I consider the interaction term between common ownership measures and the reassignment indicator. The pattern that emerges is similar to that for innovation output. The interaction term is only significant for the linear and convex versions of the GGL measures (Columns 5 and 6). With a long-run view, as summarized in Table 13, this interaction term exerts a significant effect on the growth rate of adopters' market cap in the two-year period after the reassignment, according to the concave, linear, and convex versions of GGL in Columns (1)-(3). In Columns (4) and (5), I reestimate the effect of the interaction term for one- and two-year growth rates, respectively, by instrumenting $GGL_{\text{Linear},AB}$ and its interaction with $Reass_{AB,r}$. The effect of the interaction remains positive and significant at the 1% level.

These results indicate that the effect of common ownership is driven by institutional investors that pay attention to providers' management. Their experience with these firms and their managers likely enables them to exert strong influences on managerial decisions and thereby increase the quality of the technology transfers.

[Table 13 about here.]

# 6 Common Ownership and Search and Matching Frictions

In this section, I investigate whether common ownership between technology providers and potential adopters helps alleviate the impediments that stem from search and matching frictions in the market for technology. As Akcigit, Celik and Greenwood (2016) show, reducing search and matching frictions in the market for ideas can produce substantial welfare gains. For example, for firms that want to profit from their innovation, but that cannot apply it in-house, finding another company that can benefit from the technology requires assessing potential patent assignees, which vary in visibility, according to their ability to adopt and profit from the technology. But finding such firms, especially when they are less visible, incurs search costs for the provider, which accordingly reduce the gains available from the trade. If common owners, which offer diversification and broader networks, can mitigate such frictions, the effect of common ownership should be stronger, particularly for firms that are less visible or have less information available in the public domain.

Financial analysts collect and share information about firms with the market by reporting on their activities and future prospects. Firms that attract more coverage from analysts thus should be more visible to technology providers, which reduces their search costs. If the positive effect of common ownership results from reduced search costs, which then increase the potential surplus of a deal, this benefit should be particularly salient for the invisible firms that are rarely covered by financial analysts. To test this prediction, I use an interaction term between common ownership and potential assignees' analyst coverage; its coefficient should be negative if the existence of common owners alleviates search and matching frictions.

Table 14 contains the results. For all six measures of common ownership, the interaction term with analyst coverage is positive and significant at the 1% level.[40] That is, the effect of common ownership, in terms of increasing the probability that a firm becomes the adopter, is greater if firms are followed by more analysts, such that they likely are more salient to technology providers. This finding implies that common owners reduce search costs only to a negligible extent; their ability to overcome these matching frictions does not appear to drive their positive effect on the allocation of innovative knowledge.[41]

[Table 14 about here.]

# 7 Common Ownership and Executive Common Directors

As detailed in Section 3, board connections do not drive the effect of common ownership on assignee selection. Here, I focus on the additional effect of having a common director on the two boards if this director is also either an executive of the technology provider or a potential adopter. Then, I consider the interaction of these different executive roles of shared directors with common ownership.

The informational effects of board connections are likely to influence technology transfers if shared directors serve as executives of one of the firms. Executives have more information about

[40]Estimating the probit models instead of the IV probit yields qualitatively the same results.

[41]The results in Table 14 do not necessarily imply that common owners use analyst reports to match firms in the market for technology. Rather, it is more plausible that firm management identifies potential matches, which is more likely if the firms are covered by more analysts, which makes them more visible in the market. Common ownership only affects the ultimate match, among those salient potential options, through its effect on the surplus, in that it helps alleviate the moral hazard problem linked to the transfer of know-how. This aspect explains both the robust positive interaction between analysts and common ownership and the otherwise insignificant or negative effect of common ownership in the regressions in Table 14.

the firm they are managing and more immediate control over this firm's resources compared to non-executive directors. For example, an executive director can decide to send engineers to another firm in order to help with technology adoption. She also can decide which personnel to send and for how long this service is provided.

Executive common directors also have varying incentives to internalize their actions' effects on the performance of the two firms. For instance, executives who sit on another firm's board also probably care about that firm's performance, whether because they (*i*) take their role as representatives of its shareholders seriously, (*ii*) have career concerns and want to maintain their position on the board, or (*iii*) receive remuneration linked to firm performance. Thus, sitting on another firm's board likely creates incentives to internalize the effects of managerial decisions (with regard to the firm in which the director is an executive) on the other firm's performance, similar to those evoked by common ownership. Since, in my setup, the moral hazard problem in know-how transfer stems from the management of the technology provider, I posit that if a common director is also an executive of the technology provider, then this condition contributes to the alleviation of the moral hazard problem. If common ownership and provider-executive common directors imply similar effects with regard to alleviating the moral hazard problem, such that they increase the surplus available from a potential match, these dyadic characteristics should function as substitutes in determining the probability that a transfer takes place. In other words, if two suitable adopters of the technology are available and an executive of the provider sits on one of their boards, the effect of common ownership between the provider and each potential adopter should be attenuated. Thus, I expect the interaction between common ownership and provider-executive common directors to be negative.

As Cai and Sevilir (2012) indicate in the context of M&As, executives of an acquirer might reduce asymmetric information if they also sit on the target's board, because they have access to valuable information that outside acquirers lack. In the context of technology transfers, executive directors of potential adopters who also sit on the provider's board may have better access to relevant information, by virtue of their position in the innovator's company, in which role they might talk to R&D staff, for example. Such insights likely establish a bargaining advantage in the market for technology, compared with outsiders and potential adopters without board connections. Executives of the adopters also have superior knowledge of their company's technology; by combining it with the information they can gather as directors of the provider, they likely can improve match quality, which contributes to alleviating adverse selection problems. Thus, I expect the effect of adopter-executive common directors to be complementary to common ownership and the interaction to be positive.

[Table 15 about here.]

In Table 15, I report the results for the three GGL measures that take into account the attention of common owners with respect to the provider's management.[42] In columns (1) to (3), in addition to the simple common director indicator $CD_{AB}$, I also include the indicator variables $ExecCD^A_{AB}$ and $ExecCD^B_{AB}$, which take the value 1 if a common director also serves as an executive of firm

[42] The results are qualitatively similar for the other measures.

A (provider) or B (adopter), respectively, and 0 otherwise.[43] Both indicators have positive and significant coefficients. This confirms that executives positively affect the likelihood of matching when sitting on both firms' boards.

Columns (4) to (6) of Table 15 contain the results for the interaction of common ownership with common directors that are executives of the provider. The interaction term is negative and significant at the 1% level.[44] Reflecting incentives to alleviate moral hazard, the two phenomena are substitutes. Thus, common ownership by monitoring institutions creates managerial incentives to account for the effects of managerial decisions on other firms' profits, similar to those resulting from a manager sitting on the board of this company.

In columns (7) to (9) of Table 15, I provide the coefficient of the interaction of the common ownership measures with the indicator for common directors that are executives in the adopter firm. The interaction terms for the different measures all are positive and significant at the 1% level for the concave, linear, and convex versions.[45] This interaction suggests the complementarity of these two determinants of the probability of a match. That is, adopter-executive common directors increase the probability of technology transfer through a different mechanism than common ownership does, such as by alleviating adverse selection.

Finally, including the effects of executives in Table 15, I find a significant negative effect of *non-executive* common directors in all specifications, which is consistent with findings pertaining to busy directors and firm performance (Fich and Shivdasani, 2012; Hauser, 2018).

# 8 Conclusion

By studying the effect of common ownership on the matching of firms in the market for technology, I demonstrate that common ownership between technology providers and potential adopters has economically and statistically significant effects. In particular, and as the proposed model predicts, common ownership creates incentives that motivate providers' managers to transfer uncodified know-how in ways that increase the quality of the technology transfer, which in turn increases the surplus available from the match. In anticipation of this effect, common ownership influences the selection of adopters in the market for technology. This effect is quantitatively stronger if the degree to which common owners pay attention to providers' management is accounted for by the common ownership measures.

Also consistent with the proposed model, the effect of common ownership is stronger for technologies for which the adopter more substantially relies on the transfer of uncodified know-how to benefit from the reassignment, such as recent and more complex innovations. Common ownership increases the number of future patents and citations, as well as the market cap growth of actual adopters, in support of the notion that common ownership increases the quality of technology transfers. Although this study pertains to common ownership in the context of patent reassignments, the underlying mechanism likely extends to other modes of technology transfer too, such

[43] In my sample, common directors serve as executives of at most one of the two firms.

[44] These results are qualitatively similar to the estimates from a probit model.

[45] Estimating a simple probit model yields positive estimates of the interaction term that are significant at the 1% level for all measures of common ownership.

as licensing.

Alternative mechanisms, such as reducing search costs and appointing common directors, cannot explain the positive effects of common ownership on technology reallocation. However, executive common directors have a positive impact on technology transfers between the connected firms. The interaction of these different roles of shared directors with common ownership is consistent with the proposed model of common ownership incentives. On the one hand, joint directors who are executives of the provider have incentives to ensure strong transfer quality to facilitate the adoption as they internalize the effect of the reassignment on the adopter's profits. Thus, common ownership and provider-executive common directors are substitutes in generating a match. On the other hand, the positive effect of adopter-executive common directors stems from other mechanisms, beyond alleviating the moral hazard problem in know-how transfer. They alleviate adverse selection or search and matching frictions. Thus, their effect complements the one of common ownership between firms on the matching in technology markets.

Because common ownership appears to spur the transmission of uncodified know-how and increases the quality of technology transfers, it also could lead to greater quantities of technologies being transferred, because it increases the total surplus of each deal. I leave this question for further research. Another, related research question pertains to whether innovating firms internalize the effect of diversified investors on their chances to profit from innovations that they cannot apply in their own production process, by selling them in the market for technology. This outcome would imply a positive effect on R&D investments by increasing the returns to R&D, similar to the interaction of common ownership with unintended technology spillovers (López and Vives, 2019; Antón et al., 2021*b*).

A primary focus of previous research into common ownership has been the potential for anticompetitive effects (e.g., Azar, Schmalz and Tecu, 2018), so various studies offer ideas for its regulation or limitation (Elhauge, 2016; Baker, 2016). But before such measures are taken, it is critical to gauge the economic magnitudes of the different effects of common ownership, to avoid inflicting more harm than benefits. My paper contributes to this ongoing discussion by demonstrating that common ownership of investors that pay attention to portfolio firms may alleviate moral hazard between those firms that are active in the reallocation and dissemination of innovative technological knowledge. This positive effect has to be weighed against the potential downsides of having common ownership between firms. An investigation of the trade-offs between competition and collaboration or static and dynamic efficiency promises interesting insights for future research on common ownership.

Finally, my empirical analysis indicates that monitoring institutional investors exert stronger impacts on alleviating moral hazard problems in dyadic relationships. The effects of the common ownership of institutions that supposedly pay more attention to providers' management appear stronger with regard to the adopter's market cap growth and future innovation activity. Taking this influence into account might help potential adopters gauge the value of technology transfers, which in turn can improve firm matching in the market for ideas.

# References

**Aggarwal, Reena, Sandeep Dahiya, and Nagpurnanand R Prabhala.** 2019. "The power of shareholder votes: Evidence from uncontested director elections." *Journal of Financial Economics*, 133(1): 134–153.

**Aghion, Philippe, and Peter Howitt.** 1992. "A Model of Growth Through Creative Destruction." *Econometrica*, 60(2): 323–351.

**Aghion, Philippe, John Van Reenen, and Luigi Zingales.** 2013. "Innovation and Institutional Ownership." *The American Economic Review*, 103(1): 277–304.

**Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt.** 2005. "Competition and innovation: An inverted-U relationship." *The quarterly journal of economics*, 120(2): 701–728.

**Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood.** 2016. "Buy, Keep, or Sell: Economic Growth and the Market for Ideas." *Econometrica*, 84(3): 943–984.

**Akerlof, George A, and Janet L Yellen.** 1990. "The fair wage-effort hypothesis and unemployment." *The Quarterly Journal of Economics*, 105(2): 255–283.

**Antón, Miguel, Florian Ederer, Mireia Giné, and Martin C Schmalz.** 2021*a*. "Common Ownership, Competition, and Top Management Incentives." *ECGI Working Paper Series in Finance N° 511/2017*.

**Antón, Miguel, Florian Ederer, Mireia Gine, and Martin C. Schmalz.** 2021*b*. "Innovation: The Bright Side of Common Ownership?" *SSRN Electronic Journal*.

**Appel, Ian R., Todd A. Gormley, and Donald B. Keim.** 2016. "Passive investors, not passive owners." *Journal of Financial Economics*, 121: 111–141.

**Arora, Ashish.** 1995. "Licensing tacit knowledge: Intellectual property rights and the market for know-how." *Economics of Innovation and New Technology*, 4(1): 41–60.

**Arora, Ashish, and Marco Ceccagnoli.** 2006. "Patent Protection, Complementary Assets, and Firms' Incentives for Technology Licensing." *Management Science*, 52(2): 293–308.

**Arqué-Castells, Pere, and Daniel F. Spulber.** 2021. "Firm Matching in the Market for Technology."

**Arqué-Castells, Pere, and Daniel F Spulber.** 2022. "Measuring the Private and Social Returns to R&D: Unintended Spillovers versus Technology Markets." *Journal of Political Economy*, 130(7): 1860–1918.

**Arrow, Kenneth J.** 1962. "Economic Welfare and the Allocation of Resources for Invention." In *Nelson, R.R. (Ed.), The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press, Princeton.* 609–626.

**Atanassov, Julian.** 2013. "Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting." *Journal of Finance*, 68(3): 1097–1131.

**Azar, José.** 2022. "Common Shareholders and Interlocking Directors: The Relation Between Two Corporate Networks." *Journal of Competition Law & Economics*, 18(1): 75–98.

**Azar, José.** 2017. "Portfolio Diversification, Market Power, and the Theory of the Firm." *SSRN Electronic Journal*.

**Azar, José, Martin C Schmalz, and Isabel Tecu.** 2018. "Anticompetitive Effects of Common Ownership." *The Journal of Finance*, LXXIII(4): 1513–1565.

**Backus, Matthew, Christopher Conlon, and Michael Sinkinson.** 2019. "Common Ownership in America: 1980-2017."

**Backus, Matthew, Christopher Conlon, and Michael Sinkinson.** 2020. "Theory and Measurement of Common Ownership." *AEA Papers and Proceedings*, 110(2017): 557–560.

**Baker, Jonathan B.** 2016. "Overlapping financial investor ownership, market power, and antitrust enforcement: My qualified agreement with Professor Elhauge." *Harvard Law Review*, 129(5): 212–232.

**Banal-Estañol, Albert, Inés Macho-Stadler, and David Pérez-Castrillo.** 2018. "Endogenous Matching in University-Industry Collaboration: Theory and Empirical Evidence from the United Kingdom." *Management Science*, 64(4): 1591–1608.

**Banal-Estañol, Albert, Jo Seldeslachts, and Xavier Vives.** 2022. "Ownership diversification and product market pricing Incentives." *European Corporate Governance Institute–Finance Working Paper*, , (858).

**Bena, Jan, and Kai Li.** 2014. "Corporate Innovations and Mergers and Acquisitions." *The Journal of Finance*, 69(1923-1960).

**Bertrand, Marianne, and Sendhil Mullainathan.** 2001. "Are CEOs rewarded for Luck? The ones without Principals are." *The Quarterly Journal of Economics*, , (August): 901–932.

**Booraem, Glenn.** 2013. "Passive Investors, Not Passive Owners." *https://corpgov.law.harvard.edu/2013/05/10/passive-investors-not-passive-owners/*.

**Cai, Ye, and Merih Sevilir.** 2012. "Board connections and M&A transactions." *Journal of Financial Economics*, 103(2): 327–349.

**Choi, Jay Pil.** 2001. "Technology transfer with moral hazard." *International Journal of Industrial Organization*, 19(1-2): 249–266.

**Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen.** 2008. "Boards: Does one size fit all?" *Journal of Financial Economics*, 87: 329–356.

**Contractor, Farok J, and Tagi Sagafi-Nejad.** 1981. "International technology transfer: Major issues and policy responses." *Journal of International Business Studies*, 12: 113–135.

**Conyon, Martin J.** 2015. "Shareholder say-on-pay voting and CEO compensation." Working paper, Wharton School, University of Pennsylvania.

**Elhauge, Einer.** 2016. "Horizontal Shareholding." *Harvard Law Review*, 109: 1267–1317.

**Federal Trade Commission.** 2016. "Patent Assertion Entity Activity. An FTC Study."

**Fehr, Ernst, and Simon Gächter.** 2000. "Fairness and retaliation: The economics of reciprocity." *Journal of economic perspectives*, 14(3): 159–181.

**Fich, Eliezer M, and Anil Shivdasani.** 2012. "Are busy boards effective monitors?" In *Corporate governance*. 221–258. Springer.

**Fletcher, Amelia, Martin Peitz, and Florence Thépot.** 2022. "Introduction to Special Issue on Common Ownership and Interlocking Directorates." *Journal of Competition Law & Economics*, 18(1): 1–4.

**García-Lara, Juan Manuel, Beatriz García-Osma, and Fernando Penalva.** 2009. "Accounting conservatism and corporate governance." *Review of accounting studies*, 14(1): 161–201.

**Gilje, Erik P., Todd A. Gormley, and Doron Levit.** 2020. "Who's paying attention? Measuring common ownership and its impact on managerial incentives." *Journal of Financial Economics*, 137: 152–178.

**Griliches, Zvi.** 1979. "Issues in assessing the contribution of research and development to productivity growth." *The bell journal of economics*, 92–116.

**Guo, Bing, David Pérez-Castrillo, and Anna Toldrà-Simats.** 2019. "Firms' innovation strategy under the shadow of analyst coverage." *Journal of Financial Economics*, 131(2): 456–483.

**Hall, Bronwyn H, Adam B Jaffe, and Manuel Trajtenberg.** 2001. "The NBER Patent Citations Data File: Lessons, insights and methodological tools."

**Hauser, Roie.** 2018. "Busy directors and firm performance: Evidence from mergers." *Journal of Financial Economics*, 128(1): 16–37.

**Hutschenreiter, Dennis C.** 2022. "Essays in Corporate Finance and Innovation."

**Iliev, Peter, and Michelle Lowry.** 2015. "Are mutual funds active voters?" *Review of Financial Studies*, 28(2): 446–485.

**Johnson, William C., Jonathan M. Karpoff, and Sangho Yi.** 2015. "The bonding hypothesis of takeover defenses: Evidence from IPO firms." *Journal of Financial Economics*, 117(2): 307–332.

**Kaplan, Steven N., and Luigi Zingales.** 1997. "Do investment-cash flow sensitivities provide useful measures of financing constraints?" *Quarterly Journal of Economics*, 112(1): 169–213.

**López, Ángel L., and Xavier Vives.** 2019. "Overlapping ownership, R&D spillovers, and antitrust policy." *Journal of Political Economy*, 127(5): 2394–2437.

**Macho-Stadler, Inés, Xavier Martinez-Giralt, and David Pérez-Castrillo.** 1996. "The role of information in licensing contract design." *Research Policy*, 25: 43–57.

**Nili, Yaron.** 2019. "Horizontal Directors." *Nw. UL Rev.*, 114: 1179.

**Nili, Yaron.** 2022. "Horizontal Directors Revisited." *Journal of Competition Law & Economics*, 18(1): 5–28.

**O'Brien, Daniel P., and Steven C. Salop.** 2000. "Competitive effects of partial ownership: Financial interest and corporate control." *Antitrust Law Journal*, 67(3): 559–603.

**Petajisto, Antti.** 2013. "Active share and mutual fund performance." *Financial Analysts Journal*, 69(4): 73–93.

**Romer, Paul M.** 1986. "Increasing Returns and Long-Run Growth." *Journal of Political Economy*, 94(5): 1002–1037.

**Romer, Paul Michael.** 1983. "Dynamic competitive equilibria with externalities, increasing returns, and unbounded growth." PhD diss. The University of Chicago.

**Rotemberg, Julio J.** 1984. "Financial Transaction Costs and Industrial Performance." *Working Paper, Alfred P. Sloan School of Management*, 1–36.

**Schmalz, Martin C.** 2018. "Common-ownership concentration and corporate conduct." In *Patrick Bolton (Ed.), Annual Review of Financial Economics*. Vol. 10, 413–448.

**Schmidt, Cornelius, and Rüdiger Fahlenbrach.** 2017. "Do exogenous changes in passive institutional ownership affect corporate governance and firm value?" *Journal of Financial Economics*, 124: 285–306.

**Schumpeter, J.A.** 1911. *Theorie der wirtschaftlichen Entwicklung. Eine Untersuchung über Unternehmergewinn, Kapital, Kredit, Zins und den Konjunkturzyklus.*

**Serrano, Carlos J.** 2018. "Estimating the Gains From Trade in the Market for Patent Rights." *International Economic Review*, 59(4): 1877–1904.

**Shapley, Lloyd S., and Martin Shubik.** 1972. "The assignment game I: The core." *International Journal of Game Theory*, 1(1): 111–130.

**Shekita, Nathan.** 2022. "Interventions by common owners." *Journal of Competition Law & Economics*, 18(1): 99–134.

**Teece, David J.** 1977. "Technology Transfer by Multinational Firms: The Resource Cost of Transferring Technological Know-How." *The Economic Journal*, 87(346): 242–261.

**Teece, David J.** 1986. "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy." *Research Policy*, 15(6): 285–305.

**Vives, Xavier.** 2020. "Common ownership, market power, and innovation." *International Journal of Industrial Organization*, 70.

# Table 1: Variable Definitions

| Variables | Definitions |
|---|---|
| **Dependent variables** | |
| $Reass_{AB,r}$ | Indicator variable that takes value one if firm pair $AB$ reassigns technology $r$ and zero otherwise |
| *LnPatent* | Natural logarithm of (one plus) firm's patent output |
| *LnCitation* | Natural logarithm of (one plus) firm's citation output |
| *MCGrowth* | Firm's growth rate of market capitalization |
| **Independent variables** | |
| Measures of common ownership: | |
| $\kappa_{1\%,AB}$ | Profit weight that takes into account the cross-holdings of investors that hold at least 1% of the assignor's outstanding shares |
| $GGL_{\text{FullAttention},AB}$ | GGL measure (Gilje, Gormley and Levit, 2020) that assumes full attention of investors |
| $GGL_{\text{Fitted},AB}$ | GGL measure using an attention function fitted to actual voting behavior |
| $GGL_{\text{Concave},AB}$ | GGL measure that assumes a concave attention function |
| $GGL_{\text{Linear},AB}$ | GGL measure that assumes a linear attention function |
| $GGL_{\text{Convex},AB}$ | GGL measure that assumes a convex attention function |
| Technological distance measure: | |
| $d_{B,r}$ | Distance measure weighting the distances between firm $B$ and each patent in reassignment $r$ by citations |
| Board Connections: | |
| $CD_{AB}$ | Indicator variable that takes the value one if there is a common director that serves on the boards of both firms, $A$ and B. |
| $ExecCD^{A}_{AB}$ | Indicator variable that take the value one if at least one common director is an executive of firm A, and zero otherwise. |
| $ExecCD^{B}_{AB}$ | Indicator variable that take the value one if at least one common director is an executive of firm B, and zero otherwise. |
| **Control variables** | |
| *InstOwn* | Percentage of firm's outstanding shares held by 13F institutions (Thomson Reuters s34 file) |
| *Pstock* | Natural logarithm of (one plus) the past 5-year average number of eventually granted yearly patent applications |
| *R&DtoAssets* | Firm's R&D expenses (Compustat data item ♯46) to total assets (♯6) |
| *AnalystCoverage* | Natural logarithm of (one plus) the arithmetic mean of the 12 monthly numbers of earnings forecasts obtained from financial analysts |
| *FirmSize* | Natural logarithm of the book value of total assets (♯6) at the end of the fiscal year |
| *FirmAge* | Natural logarithm of the number of years listed on Compustat |
| *Leverage* | Book value of debt (♯9 + ♯34) divided by book value of total assets (♯6) |
| *CashtoAssets* | Cash (♯1) at the end of fiscal year divided by book value of total assets (♯6) |
| *Profitability* | Operating income before depreciation (♯13) divided by book value of total stockholders' equity (♯216) |
| *PPEtoAssets* | Property, plant, and equipment (♯8) divided by book value of total assets (♯6) |
| *CapextoAssets* | Capital expenditure (♯128) divided by book value of total assets (♯6) |
| *MarketCap* | Market capitalization of equity (♯199 × ♯25) |
| *KZindex* | Kaplan and Zingales index calculated as $-1.002\times$ cash flow [(♯18 + ♯14)/♯8] plus $0.283\times$ Tobin's Q plus $3.139\times$ Leverage minus $39.368\times$ dividends [(♯21 + ♯19)/♯8] minus $1.315\times$ cash holdings (♯1/♯8), where ♯8 is lagged |
| *CGIndex* | Average of three standardized variables: the percentage of independent directors on a board, G-index, and CEO duality |
| *HHI* | Herfindahl-Hirschman Index of four-digit standard industrial classification (SIC) code |
| $HHI^2$ | Squared Herfindahl-Hirschman Index |
| $recent_r$ | Indicator variable that takes the value one if the age of the technology $r$ is below the mean age of reassigned technologies. The age of the technology is the weighted average (by application year and technology class adjusted citations) of the difference between the year of reassignment and the application year of the patents in the reassigned bundle $r$ |
| $complexity_r$ | Measure of the dispersion of patents across technology classes in the reassigned bundle given by $1-\sum_X s_X^2$, where $X$ indexes the 2-digit IPC technology classes and $s_X$ is the share of patents in a reassigned bundle $r$ that falls into the 2-digit IPC class $X$ |
| **Instrument** | |
| $PassOwnInstrument_{AB}$ | Percentage ownership of firm B's outstanding shares by pure indexers that track indexes of which firm $A$ is a constituent |

*Note:* This table details the definitions of the main variables used in the empirical analysis.

Table 2: Summary Statistics of actual Assignees.

| Variable | 25th percent. | Median | Mean | 75th percent. | Std. Dev. | No. of Obs. |
|---|---|---|---|---|---|---|
| **Dependent variable** | | | | | | |
| $Reass_{AB,r}$ | 1.000 | 1.000 | 1.000 | 1.000 | 0.000 | 191 |
| **Independent variables** | | | | | | |
| $\kappa_{1\%,AB}$ | 0.259 | 0.617 | 0.996 | 1.749 | 0.943 | 191 |
| $GGL_{\text{FullAttention},AB}$ | 2013.605 | 4114.409 | 5999.593 | 8299.659 | 4910.305 | 191 |
| $GGL_{\text{Fitted},AB}$ | 52.502 | 160.865 | 277.970 | 460.068 | 252.807 | 191 |
| $GGL_{\text{Concave},AB}$ | 45.019 | 193.436 | 584.502 | 1292.945 | 683.203 | 191 |
| $GGL_{\text{Linear},AB}$ | 1.265 | 12.478 | 85.895 | 243.095 | 120.328 | 191 |
| $GGL_{\text{Convex},AB}$ | 0.002 | 0.047 | 2.466 | 6.196 | 3.775 | 191 |
| $d_{B,r}$ | 0.049 | 0.293 | 0.321 | 0.498 | 0.269 | 191 |
| $CD_{AB}$ | 0.000 | 0.000 | 0.073 | 0.000 | 0.261 | 191 |
| **Controls** | | | | | | |
| $InstOwn_B$ | 0.497 | 0.664 | 0.675 | 0.976 | 0.269 | 191 |
| $Pstock_B$ | 2.760 | 4.755 | 4.066 | 5.344 | 1.780 | 191 |
| $R\&DtoAssets_B$ | 0.029 | 0.040 | 0.073 | 0.087 | 0.073 | 191 |
| $FirmSize_B$ | 7.544 | 9.337 | 8.688 | 10.173 | 1.853 | 191 |
| $FirmAge_B$ | 2.639 | 3.714 | 3.227 | 3.951 | 0.911 | 191 |
| $Tobin'sQ_B$ | 1.379 | 1.794 | 3.532 | 4.233 | 3.958 | 191 |
| $KZindex_B$ | -3.271 | -1.485 | -3.700 | -0.074 | 8.096 | 191 |
| $Profitability_B$ | 0.259 | 0.367 | 0.328 | 0.457 | 0.327 | 191 |
| $PPEtoAssets_B$ | 0.114 | 0.180 | 0.224 | 0.327 | 0.144 | 191 |
| $CapextoAssets_B$ | 0.022 | 0.031 | 0.051 | 0.066 | 0.053 | 191 |
| $CashtoAssets_B$ | 0.033 | 0.085 | 0.164 | 0.260 | 0.186 | 191 |
| $AnalystCoverage_B$ | 2.526 | 2.719 | 2.677 | 2.987 | 0.589 | 191 |
| $Leverage_B$ | 0.104 | 0.237 | 0.214 | 0.294 | 0.130 | 191 |
| $CGIndex_B$ | -0.026 | 0.410 | 0.285 | 0.694 | 0.525 | 191 |
| $HHI_B$ | 0.126 | 0.361 | 0.455 | 0.861 | 0.321 | 191 |
| $HHI_B^2$ | 0.016 | 0.130 | 0.310 | 0.741 | 0.331 | 191 |

*Note:* This table provides the descriptive statistics for the variables included in the baseline probit regressions for actual assignees in the market for technology during 1990-2006.

Table 3: Comparison of actual and counterfactual Assignees and actual Assignors.

| Sample: | Assignees | Counterfactuals | | | Assignors | | |
|---|---|---|---|---|---|---|---|
| Variable | Mean | Min | Mean | Max | Min | Mean | Max |
| **Dependent variable** | | | | | | | |
| $Reass_{AB,r}$ | 1.000 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| **Ownership** | | | | | | | |
| $\kappa_{1\%,AB}$ | 0.996 | 0.000 | 0.609 | 20.891 | | | |
| $GGL_{\text{FullAttention},AB}$ | 5999.593 | 0.000 | 3200.321 | 39683.627 | | | |
| $GGL_{\text{Fitted},AB}$ | 277.970 | 0.000 | 127.861 | 2543.245 | | | |
| $GGL_{\text{Concave},AB}$ | 584.502 | 0.000 | 221.916 | 6091.315 | | | |
| $GGL_{\text{Linear},AB}$ | 85.895 | 0.000 | 29.763 | 1627.122 | | | |
| $GGL_{\text{Convex},AB}$ | 2.466 | 0.000 | 0.980 | 116.210 | | | |
| $InstOwn_B$ | 0.675 | 0.000 | 0.518 | 1.000 | | | |
| **Board connections** | | | | | | | |
| $CD_{AB}$ | 0.073 | 0.000 | 0.015 | 1.000 | | | |
| **Technology** | | | | | | | |
| $d_{B,r}$ | 0.321 | 0.000 | 0.526 | 0.994 | | | |
| $Pstock$ | 4.066 | 0.182 | 2.045 | 8.261 | | | |
| **Controls** | | | | | | | |
| *R&DtoAssets* | 0.073 | 0.000 | 0.096 | 1.744 | 0.003 | 0.082 | 1.334 |
| *AnalystCoverage* | 2.677 | 0.000 | 2.023 | 3.847 | 0.000 | 2.448 | 3.847 |
| *FirmSize* | 8.688 | 2.311 | 6.953 | 13.081 | 2.934 | 9.548 | 13.529 |
| *FirmAge* | 3.227 | 0.000 | 2.912 | 4.025 | 1.386 | 3.330 | 4.007 |
| *Tobin'sQ* | 3.532 | 0.341 | 3.421 | 29.494 | 0.523 | 2.375 | 24.088 |

*Note:* This table contains the descriptive statistics of key variables used to compare actual assignees and counterfactuals, along with assignor firm characteristics.

Table 4: Correlation between Common Ownership Measures.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) $\kappa_{1\%,AB}$ | 1.000 | | | | | |
| (2) $GGL_{\text{FullAttention},AB}$ | 0.355 | 1.000 | | | | |
| (3) $GGL_{\text{Fitted},AB}$ | 0.423 | 0.901 | 1.000 | | | |
| (4) $GGL_{\text{Concave},AB}$ | 0.445 | 0.582 | 0.803 | 1.000 | | |
| (5) $GGL_{\text{Linear},AB}$ | 0.392 | 0.382 | 0.619 | 0.960 | 1.000 | |
| (6) $GGL_{\text{Convex},AB}$ | 0.328 | 0.285 | 0.486 | 0.857 | 0.950 | 1.000 |

*Note:* This table reports the correlation coefficients for the different common ownership measures.

Table 5: Baseline results: Common Ownership and Reassignments.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | 0.250*** | | | | | |
| | (0.071) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000*** | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.002*** | | | |
| | | | (0.000) | | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.001*** | | |
| | | | | (0.000) | | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.004** | |
| | | | | | (0.002) | |
| $GGL_{\text{Convex},AB}$ | | | | | | 0.028** |
| | | | | | | (0.011) |
| $CD_{AB}$ | 0.415* | 0.361 | 0.340 | 0.324 | 0.368 | 0.416* |
| | (0.246) | (0.243) | (0.245) | (0.250) | (0.248) | (0.244) |
| $InstOwn_B$ | 0.747** | 0.468 | 0.455* | 0.510** | 0.788*** | 0.996*** |
| | (0.313) | (0.292) | (0.273) | (0.244) | (0.263) | (0.310) |
| $d_{B,r}$ | -2.113*** | -2.164*** | -2.200*** | -2.151*** | -2.110*** | -2.091*** |
| | (0.248) | (0.249) | (0.253) | (0.255) | (0.250) | (0.251) |
| $Pstock_B$ | 0.347*** | 0.353*** | 0.354*** | 0.345*** | 0.348*** | 0.355*** |
| | (0.035) | (0.036) | (0.036) | (0.035) | (0.035) | (0.036) |
| $R\&DtoAssets_B$ | -0.380 | -0.360 | -0.463 | -0.927 | -0.819 | -0.420 |
| | (0.590) | (0.593) | (0.664) | (0.840) | (0.733) | (0.592) |
| $AnalystCoverage_B$ | 0.125 | 0.088 | 0.105 | 0.130 | 0.103 | 0.071 |
| | (0.090) | (0.087) | (0.086) | (0.088) | (0.085) | (0.084) |
| $FirmSize_B$ | -0.005 | -0.022 | -0.024 | -0.030 | -0.022 | -0.012 |
| | (0.044) | (0.044) | (0.045) | (0.045) | (0.044) | (0.043) |
| $FirmAge_B$ | -0.257*** | -0.263*** | -0.280*** | -0.288*** | -0.265*** | -0.246*** |
| | (0.074) | (0.074) | (0.075) | (0.080) | (0.078) | (0.074) |
| $Tobin'sQ_B$ | 0.006 | 0.009 | 0.010 | 0.009 | 0.007 | 0.006 |
| | (0.011) | (0.010) | (0.010) | (0.010) | (0.010) | (0.011) |
| $KZindex_B$ | -0.001 | -0.002 | -0.002 | -0.003 | -0.002 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $Profitability_B$ | -0.059 | -0.034 | -0.014 | -0.009 | -0.033 | -0.059 |
| | (0.078) | (0.082) | (0.083) | (0.085) | (0.082) | (0.079) |
| $PPEtoAssets_B$ | -0.552 | -0.542 | -0.488 | -0.427 | -0.539 | -0.649 |
| | (0.419) | (0.433) | (0.434) | (0.448) | (0.440) | (0.426) |
| $CapextoAssets_B$ | 0.629 | 0.572 | 0.489 | 0.582 | 0.697 | 0.708 |
| | (1.292) | (1.348) | (1.372) | (1.350) | (1.307) | (1.302) |
| $CashtoAssets_B$ | -0.199 | -0.226 | -0.274 | -0.297 | -0.244 | -0.186 |
| | (0.307) | (0.303) | (0.312) | (0.318) | (0.309) | (0.298) |
| $Leverage_B$ | 0.400** | 0.361* | 0.357* | 0.363** | 0.389** | 0.399** |
| | (0.165) | (0.205) | (0.209) | (0.185) | (0.167) | (0.163) |
| $CGIndex_B$ | -0.210*** | -0.215*** | -0.225*** | -0.228*** | -0.224*** | -0.215*** |
| | (0.081) | (0.083) | (0.084) | (0.082) | (0.080) | (0.079) |
| $HHI_B$ | -0.425 | -0.301 | -0.302 | -0.521 | -0.568 | -0.474 |
| | (0.588) | (0.603) | (0.625) | (0.638) | (0.606) | (0.585) |
| $HHI_B^2$ | 1.227** | 1.118** | 1.064* | 1.178** | 1.260** | 1.250** |
| | (0.516) | (0.527) | (0.548) | (0.560) | (0.533) | (0.510) |
| Constant | -1.760*** | -1.322*** | -1.357*** | -1.342*** | -1.426*** | -1.525*** |
| | (0.361) | (0.367) | (0.377) | (0.374) | (0.367) | (0.365) |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 19179 | 19179 | 19179 | 19179 | 19179 | 19179 |
| $Pseudo-R^2$ | 0.314 | 0.322 | 0.332 | 0.336 | 0.319 | 0.303 |

*Note:* This table provides coefficient estimates for different common ownership measures from the probit model in Equation (8), using the full sample of actual and counterfactual dyads of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for dyads that form the control group. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Common Ownership and Reassignments without Board Connections.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | 0.265*** | | | | | |
| | (0.074) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000*** | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.002*** | | | |
| | | | (0.000) | | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.001*** | | |
| | | | | (0.000) | | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.004** | |
| | | | | | (0.002) | |
| $GGL_{\text{Convex},AB}$ | | | | | | 0.032*** |
| | | | | | | (0.012) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 17021 | 17021 | 17021 | 17021 | 17021 | 17021 |
| $Pseudo-R^2$ | 0.319 | 0.326 | 0.337 | 0.342 | 0.325 | 0.307 |

*Note:* This table contains the coefficient estimates for the different common ownership measures from the probit model in Equation (8), using the sample of actual and counterfactual dyads of technology providers and potential adopters in the full sample, excluding dyads with board connections. The dependent variable $Reass_{AB,r}$ is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for the dyads that form the control group. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: IV First Stage.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\kappa_{1\%,AB}$ | $GGL_{\text{FullAttention},AB}$ | $GGL_{\text{Fitted},AB}$ | $GGL_{\text{Concave},AB}$ | $GGL_{\text{Linear},AB}$ | $GGL_{\text{Convex},AB}$ |
| $PassOwnInstrument_{AB}$ | 0.193*** | 481.332*** | 29.592*** | 69.597*** | 11.278*** | 0.420*** |
| | (0.020) | (86.957) | (4.356) | (10.326) | (1.902) | (0.090) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 |
| *Adjusted* $R^2$ | 0.375 | 0.500 | 0.549 | 0.763 | 0.808 | 0.753 |
| F - statistic | 69.944 | 69.949 | 69.237 | 43.851 | 29.958 | 25.164 |

*Note:* This table provides the coefficient ordinary least squares estimates for the instrumental variable from the model in Equation (9), reflecting the first-stage regression of the IV, using the sample of actual and counterfactual dyads of technology providers and potential adopters in the full sample, for which there is index-constituent information. The dependent variables are the different measures of common ownership. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: IV Second Stage: Common Ownership and Reassignments.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | 0.928** | | | | | |
| | (0.368) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000*** | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.006*** | | | |
| | | | (0.002) | | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.003*** | | |
| | | | | (0.001) | | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.018*** | |
| | | | | | (0.007) | |
| $GGL_{\text{Convex},AB}$ | | | | | | 0.487*** |
| | | | | | | (0.123) |
| $CD_{AB}$ | 0.347 | 0.153 | 0.121 | 0.057 | 0.044 | -0.315 |
| | (0.320) | (0.278) | (0.310) | (0.400) | (0.451) | (0.410) |
| $InstOwn_B$ | 0.690* | -0.319 | 0.124 | 0.458 | 0.744** | 1.143*** |
| | (0.403) | (0.577) | (0.469) | (0.371) | (0.327) | (0.293) |
| $d_{B,r}$ | -2.404*** | -2.025*** | -2.237*** | -2.409*** | -2.411*** | -2.158*** |
| | (0.306) | (0.424) | (0.363) | (0.332) | (0.337) | (0.352) |
| $Pstock_B$ | 0.340*** | 0.293*** | 0.323*** | 0.338*** | 0.342*** | 0.333*** |
| | (0.041) | (0.064) | (0.052) | (0.044) | (0.044) | (0.048) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 |
| p-value exogeneity | 0.181 | 0.036 | 0.070 | 0.284 | 0.375 | 0.022 |

*Note:* This table contains coefficient estimates for the different common ownership measures from the IV probit model in Equation (10), using the identification strategy described in Section 2.2 and the full sample of actual and counterfactual dyads of technology providers and potential adopters for which index-constituent information is available. The dependent variable $Reass_{AB,r}$ is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for dyads that form the control group. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Common Ownership and Recent Technologies (IV Probit Second Stage).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | -0.979** | | | | | |
| | (0.479) | | | | | |
| $\kappa_{1\%,AB}$ | 3.243*** | | | | | |
| $\times recent_r$ | (0.497) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000 | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.001*** | | | | |
| $\times recent_r$ | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | -0.001 | | | |
| | | | (0.004) | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.012*** | | | |
| $\times recent_r$ | | | (0.003) | | | |
| $GGL_{\text{Concave},AB}$ | | | | -0.003 | | |
| | | | | (0.003) | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.008*** | | |
| $\times recent_r$ | | | | (0.002) | | |
| $GGL_{\text{Linear},AB}$ | | | | | -0.048 | |
| | | | | | (0.029) | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.071*** | |
| $\times recent_r$ | | | | | (0.019) | |
| $GGL_{\text{Convex},AB}$ | | | | | | -0.855 |
| | | | | | | (1.402) |
| $GGL_{\text{Convex},AB}$ | | | | | | 1.421 |
| $\times recent_r$ | | | | | | (1.179) |
| $recent_r$ | -3.398*** | -1.716*** | -0.988 | -1.584* | -2.157*** | -1.306 |
| | (0.419) | (0.431) | (0.616) | (0.812) | (0.811) | (1.013) |
| $CD_{AB}$ | -0.163 | -0.075 | -0.103 | 0.283 | 0.396 | -0.453 |
| | (0.265) | (0.306) | (0.328) | (0.430) | (0.483) | (0.422) |
| $InstOwn_B$ | 0.591* | 0.042 | 0.164 | 0.715 | 0.871*** | 1.026*** |
| | (0.339) | (0.884) | (0.676) | (0.530) | (0.262) | (0.260) |
| $d_{B,r}$ | -2.058*** | -2.262*** | -2.400*** | -2.376*** | -1.970*** | -1.968*** |
| | (0.306) | (0.327) | (0.313) | (0.406) | (0.706) | (0.507) |
| $Pstock_B$ | 0.295*** | 0.308*** | 0.317*** | 0.304*** | 0.256** | 0.296*** |
| | (0.037) | (0.049) | (0.043) | (0.052) | (0.101) | (0.077) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 |
| p-value exogeneity | 0.000 | 0.002 | 0.012 | 0.184 | 0.107 | 0.000 |

*Note:* This table reveals the coefficient estimates for the different common ownership measures and their interaction with an indicator variable for recent innovations from the IV probit model in Equation (10), using the identification strategy described in Section 2.2 and the full sample of actual and counterfactual dyads of technology providers and potential adopters for which index-constituent information are available. The dependent variable $Reass_{AB,r}$ is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for dyads that form the control group. The indicator variable $recent_r$ takes a value of 1 if the reassigned technology is younger than the median of the sample. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Common Ownership, Reassignments, and Adopters' Future Innovation (1).

| | (1) *LnPatent* t | (2) *LnCitation* t | (3) *LnPatent* t | (4) *LnCitation* t | (5) *LnPatent* t | (6) *LnCitation* t | (7) *LnPatent* t | (8) *LnCitation* t | (9) *LnPatent* t | (10) *LnCitation* t | (11) *LnPatent* t | (12) *LnCitation* t |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Reass_{AB,r}$ | 0.050 | 0.062 | 0.067 | 0.071 | 0.032 | 0.047 | -0.031 | -0.011 | 0.026 | 0.041 | 0.063 | 0.074 |
| | (0.078) | (0.084) | (0.088) | (0.098) | (0.095) | (0.099) | (0.093) | (0.098) | (0.080) | (0.087) | (0.077) | (0.085) |
| $\kappa_{1\%,AB}$ | -0.001 | -0.003 | | | | | | | | | | |
| | (0.004) | (0.005) | | | | | | | | | | |
| $Reass_{AB,r} \times \kappa_{1\%,AB}$ | 0.108 | 0.060 | | | | | | | | | | |
| | (0.087) | (0.083) | | | | | | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | | -0.000** | -0.000** | | | | | | | | |
| | | | (0.000) | (0.000) | | | | | | | | |
| $Reass_{AB,r} \times GGL_{\text{FullAttention},AB}$ | | | 0.000 | 0.000 | | | | | | | | |
| | | | (0.000) | (0.000) | | | | | | | | |
| $GGL_{\text{Fitted},AB}$ | | | | | -0.000** | -0.000** | | | | | | |
| | | | | | (0.000) | (0.000) | | | | | | |
| $Reass_{AB,r} \times GGL_{\text{Fitted},AB}$ | | | | | 0.001 | 0.001 | | | | | | |
| | | | | | (0.001) | (0.001) | | | | | | |
| $GGL_{\text{Concave},AB}$ | | | | | | | -0.000** | -0.000** | | | | |
| | | | | | | | (0.000) | (0.000) | | | | |
| $Reass_{AB,r} \times GGL_{\text{Concave},AB}$ | | | | | | | 0.001** | 0.001** | | | | |
| | | | | | | | (0.000) | (0.000) | | | | |
| $GGL_{\text{Linear},AB}$ | | | | | | | | | -0.000* | -0.000* | | |
| | | | | | | | | | (0.000) | (0.000) | | |
| $Reass_{AB,r} \times GGL_{\text{Linear},AB}$ | | | | | | | | | 0.007*** | 0.006*** | | |
| | | | | | | | | | (0.002) | (0.002) | | |
| $GGL_{\text{Convex},AB}$ | | | | | | | | | | | -0.000 | -0.000 |
| | | | | | | | | | | | (0.000) | (0.000) |
| $Reass_{AB,r} \times GGL_{\text{Convex},AB}$ | | | | | | | | | | | 0.208*** | 0.190*** |
| | | | | | | | | | | | (0.048) | (0.051) |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm pair-FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year-FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 253058 | 253058 | 337075 | 337075 | 337075 | 337075 | 337075 | 337075 | 337075 | 33707 5 | 337075 | 337075 |
| *Adjusted* $R^2$ | 0.831 | 0.796 | 0.818 | 0.783 | 0.818 | 0.783 | 0.818 | 0.783 | 0.818 | 0.7 83 | 0.817 | 0.783 |

*Note:* This table reveals the ordinary least squares coefficient estimates for different common ownership measures and their interaction with the indicator variable $Reass_{AB,r}$ which equals 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ in year $t$ and 0 otherwise. The sample is a dyadic panel of all actual traders and control pairs. The dependent variables are the natural logarithm of (1 +) the number of patents and citations, respectively, for which a potential adopter applied in year $t$ (for patents granted afterward). All specifications include year and dyadic fixed effects. Robust standard errors (clustered at the firm-pair level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Common Ownership, Reassignments, and Adopters' Future Innovation (2).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *LnPatent* | *LnCitation* | *LnPatent* | *LnCitation* | *LnPatent* | *LnCitation* | *LnPatent* | *LnCitation* | *LnPatent* | *LnCitation* | *LnPatent* | *LnCitation* |
| | t+1 | t+1 | t+2 | t+2 | t+1 | t+1 | t+2 | t+2 | t+1 | t+1 | t+2 | t+2 |
| | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | IV | IV | IV | IV |
| $Reass_{AB,r}$ | 0.172* | 0.107 | 0.185* | 0.076 | 0.201** | 0.127 | 0.210** | 0.092 | -0.369* | -0.421 | -0.450** | -0.462 |
| | (0.094) | (0.126) | (0.107) | (0.144) | (0.091) | (0.120) | (0.102) | (0.137) | (0.218) | (0.295) | (0.228) | (0.329) |
| $GGL_{\text{Linear},AB}$ | -0.000 | -0.000 | -0.000 | -0.000 | | | | | -0.037*** | -0.061*** | -0.042*** | -0.066*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | | | | | (0.010) | (0.013) | (0.011) | (0.014) |
| $Reass_{AB,r}$ | 0.006*** | 0.005*** | 0.005*** | 0.004*** | | | | | 0.033*** | 0.034** | 0.036*** | 0.033** |
| $\times\ GGL_{\text{Linear},AB}$ | (0.002) | (0.001) | (0.002) | (0.001) | | | | | (0.007) | (0.013) | (0.008) | (0.016) |
| $GGL_{\text{Convex},AB}$ | | | | | -0.000 | -0.000 | -0.000 | -0.000 | | | | |
| | | | | | (0.000) | (0.000) | (0.000) | (0.000) | | | | |
| $Reass_{AB,r}$ | | | | | 0.203*** | 0.146*** | 0.173*** | 0.124*** | | | | |
| $\times\ GGL_{\text{Convex},AB}$ | | | | | (0.048) | (0.038) | (0.050) | (0.039) | | | | |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm pair-FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year-FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 244323 | 204453 | 244323 | 204453 | 244323 | 204453 | 244323 | 204453 | 147229 | 122412 | 147229 | 122412 |
| *Adjusted* $R^2$ | 0.854 | 0.861 | 0.821 | 0.826 | 0.854 | 0.861 | 0.821 | 0.826 | -0.035 | 0.007 | 0.017 | -0.049 |
| Kleibergen-Paap F | | | | | | | | | 14.278 | 9.072 | 14.278 | 9.072 |



*Note:* This table contains both ordinary least squares (OLS) and IV coefficient estimates for different common ownership measures and their interaction with the indicator variable $Reass_{AB,r}$ which is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ in year $t$ and 0 otherwise. The sample is a dyadic panel of all actual traders and control pairs. The dependent variables are the natural logarithm of (1 +) the number of patents and citations, respectively, for which a potential adopter applied in year $t+1$ and $t+2$ (for patents granted afterward). All specifications include year and dyadic fixed effects. Robust standard errors (clustered at the firm-pair level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Common Ownership, Reassignments, and Adopters' Market Cap Growth (1).

| | (1) *MCGrowth* $t$ *to* $t+1$ | (2) *MCGrowth* $t$ *to* $t+1$ | (3) *MCGrowth* $t$ *to* $t+1$ | (4) *MCGrowth* $t$ *to* $t+1$ | (5) *MCGrowth* $t$ *to* $t+1$ | (6) *MCGrowth* $t$ *to* $t+1$ |
|---|---|---|---|---|---|---|
| $Reass_{AB,r}$ | -0.196 | -0.255 | -0.272 | -0.310* | -0.300* | -0.286* |
| | (0.148) | (0.186) | (0.179) | (0.180) | (0.170) | (0.163) |
| $\kappa_{1\%,AB}$ | -0.070 | | | | | |
| | (0.061) | | | | | |
| $Reass_{AB,r}$ $\times\ \kappa_{1\%,AB}$ | -0.064 | | | | | |
| | (0.205) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000 | | | | |
| | | (0.000) | | | | |
| $Reass_{AB,r}$ $\times\ GGL_{\text{FullAttention},AB}$ | | 0.000 | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.000* | | | |
| | | | (0.000) | | | |
| $Reass_{AB,r}$ $\times\ GGL_{\text{Fitted},AB}$ | | | 0.000 | | | |
| | | | (0.000) | | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.000** | | |
| | | | | (0.000) | | |
| $Reass_{AB,r}$ $\times\ GGL_{\text{Concave},AB}$ | | | | 0.000 | | |
| | | | | (0.000) | | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.000 | |
| | | | | | (0.000) | |
| $Reass_{AB,r}$ $\times\ GGL_{\text{Linear},AB}$ | | | | | 0.004** | |
| | | | | | (0.002) | |
| $GGL_{\text{Convex},AB}$ | | | | | | -0.000 |
| | | | | | | (0.000) |
| $Reass_{AB,r}$ $\times\ GGL_{\text{Convex},AB}$ | | | | | | 0.134*** |
| | | | | | | (0.048) |
| Controls | YES | YES | YES | YES | YES | YES |
| Firm pair-FE | YES | YES | YES | YES | YES | YES |
| Year-FE | YES | YES | YES | YES | YES | YES |
| Observations | 223236 | 223236 | 223236 | 223236 | 223236 | 223236 |
| *Adjusted* $R^2$ | 0.406 | 0.406 | 0.406 | 0.406 | 0.406 | 0.406 |

*Note:* This table provides ordinary least squares coefficient estimates for the different common ownership measures and their interaction with the indicator variable $Reass_{AB,r}$ which is equal to 1 for dyads $AB$ that engage in the transfer of the reassignment $r$ in year $t$ and 0 otherwise. The sample is a dyadic panel of all actual traders and control pairs. The dependent variable is the market capitalization growth rate of the adopter one year after the (potential) reassignment. All specifications include year and dyadic fixed effects. Robust standard errors (clustered at the firm-pair level) are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Common Ownership, Reassignments, and Adopters' Market Cap Growth (2).

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | *MCGrowth* | *MCGrowth* | *MCGrowth* | *MCGrowth* | *MCGrowth* |
| | $t$ *to* $t+2$ | $t$ *to* $t+2$ | $t$ *to* $t+2$ | $t$ *to* $t+1$ | $t$ *to* $t+2$ |
| | *OLS* | *OLS* | *OLS* | *IV* | *IV* |
| $Reass_{AB,r}$ | -0.641* | -0.524* | -0.467* | -0.858** | -1.522** |
| | (0.352) | (0.301) | (0.282) | (0.337) | (0.599) |
| $GGL_{\text{Concave},AB}$ | 0.000 | | | | |
| | (0.000) | | | | |
| $Reass_{AB,r}$ | 0.001** | | | | |
| $\times\ GGL_{\text{Concave},AB}$ | (0.001) | | | | |
| $GGL_{\text{Linear},AB}$ | | 0.000 | | -0.044*** | -0.090*** |
| | | (0.000) | | (0.016) | (0.025) |
| $Reass_{AB,r}$ | | 0.007** | | 0.032*** | 0.056*** |
| $\times\ GGL_{\text{Linear},AB}$ | | (0.003) | | (0.011) | (0.021) |
| $GGL_{\text{Convex},AB}$ | | | -0.000 | | |
| | | | (0.000) | | |
| $Reass_{AB,r}$ | | | 0.176** | | |
| $\times\ GGL_{\text{Convex},AB}$ | | | (0.072) | | |
| Controls | YES | YES | YES | YES | YES |
| Firm pair-FE | YES | YES | YES | YES | YES |
| Year-FE | YES | YES | YES | YES | YES |
| Observations | 211299 | 211299 | 211299 | 197525 | 187475 |
| *Adjusted* $R^2$ | 0.390 | 0.390 | 0.390 | -0.015 | -0.041 |
| Kleibergen-Paap F | | | | 19.606 | 18.476 |

*Note:* This table reports OLS and IV coefficient estimates for different common ownership measures and their interaction with the indicator variable $Reass_{AB,r}$ which is equal to 1 for the dyad $AB$ that engages in the transfer of the reassignment $r$ in year $t$ and 0 otherwise. The sample is a dyadic panel for all actual traders and control pairs. The dependent variable is the market capitalization growth rate of the adopter within one or two years after the (potential) reassignment. All specifications include year and firm-pair fixed effects. Robust standard errors (clustered at the firm-pair level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Common Ownership and Analyst Coverage (IV Probit Second Stage).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | -3.614*** | | | | | |
| | (1.244) | | | | | |
| $\kappa_{1\%,AB}$ $\times AnalystCoverage_B$ | 1.626*** | | | | | |
| | (0.420) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | -0.000* | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{FullAttention},AB}$ $\times AnalystCoverage_B$ | | 0.000*** | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | -0.009** | | | |
| | | | (0.004) | | | |
| $GGL_{\text{Fitted},AB}$ $\times AnalystCoverage_B$ | | | 0.004*** | | | |
| | | | (0.001) | | | |
| $GGL_{\text{Concave},AB}$ | | | | -0.005 | | |
| | | | | (0.003) | | |
| $GGL_{\text{Concave},AB}$ $\times AnalystCoverage_B$ | | | | 0.003*** | | |
| | | | | (0.001) | | |
| $GGL_{\text{Linear},AB}$ | | | | | -0.042 | |
| | | | | | (0.027) | |
| $GGL_{\text{Linear},AB}$ $\times AnalystCoverage_B$ | | | | | 0.020*** | |
| | | | | | (0.007) | |
| $GGL_{\text{Convex},AB}$ | | | | | | -1.779*** |
| | | | | | | (0.283) |
| $GGL_{\text{Convex},AB}$ $\times AnalystCoverage_B$ | | | | | | 0.680*** |
| | | | | | | (0.081) |
| $AnalystCoverage_B$ | -0.875*** | -0.532** | -0.332* | -0.178 | -0.111 | -0.262*** |
| | (0.299) | (0.229) | (0.177) | (0.193) | (0.202) | (0.073) |
| $CD_{AB}$ | 0.262 | 0.382 | 0.469 | 0.567 | 0.711 | 0.354 |
| | (0.271) | (0.298) | (0.313) | (0.424) | (0.466) | (0.308) |
| $InstOwn_B$ | 1.269*** | 1.146* | 1.296** | 0.945* | 0.909*** | 0.836*** |
| | (0.280) | (0.642) | (0.520) | (0.496) | (0.332) | (0.245) |
| $d_{B,r}$ | -1.446* | -2.277*** | -2.334*** | -2.331*** | -2.168*** | -1.093** |
| | (0.827) | (0.308) | (0.317) | (0.365) | (0.538) | (0.507) |
| $Pstock_B$ | 0.192 | 0.321*** | 0.338*** | 0.326*** | 0.302*** | 0.186** |
| | (0.127) | (0.046) | (0.047) | (0.053) | (0.074) | (0.078) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 |
| p-value exogeneity | 0.013 | 0.031 | 0.088 | 0.488 | 0.444 | 0.000 |

*Note:* This table reports coefficient estimates for the different common ownership measures and their interaction with the variable $AnalystCoverage_B$ from the IV probit model in Equation (10) using the identification strategy described in Section 2.2 and the full sample of actual and counterfactual firm pairs of technology providers and potential adopters for which index constituent information are available. The dependent variable $Reass_{AB,r}$ is equal to 1 for the dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for the control pairs. The variable $AnalystCoverage_B$ is the natural logarithm of (1 +) the arithmetic mean of the 12 monthly numbers of earnings forecasts the potential adopter obtained from financial analysts. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Common Ownership and Executive Common Directors (IV Probit Second Stage).

| | (1) $Reass_{AB,r}$ | (2) $Reass_{AB,r}$ | (3) $Reass_{AB,r}$ | (4) $Reass_{AB,r}$ | (5) $Reass_{AB,r}$ | (6) $Reass_{AB,r}$ | (7) $Reass_{AB,r}$ | (8) $Reass_{AB,r}$ | (9) $Reass_{AB,r}$ |
|---|---|---|---|---|---|---|---|---|---|
| $GGL_{\text{Concave},AB}$ | 0.004*** | | | 0.004*** | | | 0.004*** | | |
| | (0.001) | | | (0.001) | | | (0.001) | | |
| $GGL_{\text{Concave},AB}$ $\times ExecCD^A_{AB}$ | | | | -0.193*** | | | | | |
| | | | | (0.015) | | | | | |
| $GGL_{\text{Concave},AB}$ $\times ExecCD^B_{AB}$ | | | | | | | 0.077*** | | |
| | | | | | | | (0.006) | | |
| $GGL_{\text{Linear},AB}$ | | 0.023*** | | | 0.024*** | | | 0.023*** | |
| | | (0.006) | | | (0.006) | | | (0.006) | |
| $GGL_{\text{Linear},AB}$ $\times ExecCD^A_{AB}$ | | | | | -1.616*** | | | | |
| | | | | | (0.127) | | | | |
| $GGL_{\text{Linear},AB}$ $\times ExecCD^B_{AB}$ | | | | | | | | 2.211*** | |
| | | | | | | | | (0.784) | |
| $GGL_{\text{Convex},AB}$ | | | 0.580*** | | | 0.603*** | | | 0.498*** |
| | | | (0.106) | | | (0.099) | | | (0.113) |
| $GGL_{\text{Convex},AB}$ $\times ExecCD^A_{AB}$ | | | | | | -191.358*** | | | |
| | | | | | | (26.409) | | | |
| $GGL_{\text{Convex},AB}$ $\times ExecCD^B_{AB}$ | | | | | | | | | 2853.531*** |
| | | | | | | | | | (780.422) |
| $ExecCD^A_{AB}$ | 4.389*** | 4.566*** | 4.510*** | 33.619*** | 18.925*** | 12.504*** | 4.374*** | 4.547*** | 3.808*** |
| | (0.969) | (0.999) | (0.799) | (2.300) | (1.183) | (1.321) | (0.968) | (0.995) | (0.712) |
| $ExecCD^B_{AB}$ | 2.113** | 2.110** | 2.211*** | 2.182** | 2.198** | 2.248*** | -9.507*** | -12.044*** | -48.197*** |
| | (0.899) | (0.940) | (0.799) | (0.877) | (0.921) | (0.774) | (1.087) | (3.480) | (16.795) |
| $CD_{AB}$ | -1.064** | -1.143** | -1.389*** | -1.145*** | -1.241*** | -1.448*** | -1.056** | -1.142** | -1.196*** |
| | (0.436) | (0.485) | (0.392) | (0.422) | (0.468) | (0.375) | (0.438) | (0.486) | (0.371) |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 | 14620 |
| p-value exogeneity | 0.070 | 0.116 | 0.003 | 0.108 | 0.182 | 0.005 | 0.096 | 0.096 | 0.000 |

*Note:* This table reports coefficient estimates for different common ownership measures and the indicators for executive common directors and the corresponding interactions using the identification strategy described in Section 2.2 and the full sample of actual and counterfactual firm pairs of technology providers and potential adopters for which index constituent information are available. The dependent variable $Reass_{AB,r}$ is equal to 1 for the dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for the control pairs. The indicator $CD_{AB}$ takes the value 1 if the firm pair has at least one common director and 0 otherwise. The dummy variable $ExecCD^A_{AB}$ ($ExecCD^B_{AB}$) takes the value 1 if a common director is also an executive of the provider (adopter) and 0 otherwise. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

# A Appendix

## A.1 Derivation of firms' objective function (11)

Let $W_i = \sum_l \beta_{il} \mathit{\Pi}_l$ be the wealth of investor $i$. When the manager of firm $j$ maximizes a weighted average of its investors' wealth, then he solves the following program:

$$\max \sum_i \gamma_{ij} W_i = \max \sum_i \gamma_{ij} \sum_l \beta_{il} \mathit{\Pi}_l \tag{27}$$

$$= \max \sum_i \gamma_{ij} \beta_{ij} \mathit{\Pi}_j + \sum_i \gamma_{ij} \sum_{l \neq j} \beta_{il} \mathit{\Pi}_l \tag{28}$$

$$= \max \mathit{\Pi}_j \sum_i \gamma_{ij} \beta_{ij} + \sum_{l \neq j} \sum_i \gamma_{ij} \beta_{il} \mathit{\Pi}_l \tag{29}$$

$$\propto \max \mathit{\Pi}_j + \sum_{l \neq j} \frac{\sum_i \gamma_{ij} \beta_{il}}{\sum_i \gamma_{ij} \beta_{ij}} \mathit{\Pi}_l. \tag{30}$$

Considering firm $j = A$ and firms $B_l$, where $l = 1, 2, ..., n$, and denoting $\lambda_{AB_l} \equiv \frac{\sum_i \gamma_{iA} \beta_{il}}{\sum_i \gamma_{iA} \beta_{iA}}$ yields equation (11).

Table 16: Common Ownership and Complex Technologies (Probit).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ | $Reass_{AB,r}$ |
| $\kappa_{1\%,AB}$ | 0.008 | | | | | |
| | (0.115) | | | | | |
| $\kappa_{1\%,AB}$ | 0.787** | | | | | |
| $\times$ $complexity_r$ | (0.318) | | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000 | | | | |
| | | (0.000) | | | | |
| $GGL_{\text{FullAttention},AB}$ | | 0.000 | | | | |
| $\times$ $complexity_r$ | | (0.000) | | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.001 | | | |
| | | | (0.000) | | | |
| $GGL_{\text{Fitted},AB}$ | | | 0.002 | | | |
| $\times$ $complexity_r$ | | | (0.001) | | | |
| $GGL_{\text{Concave},AB}$ | | | | -0.000 | | |
| | | | | (0.000) | | |
| $GGL_{\text{Concave},AB}$ | | | | 0.003** | | |
| $\times$ $complexity_r$ | | | | (0.001) | | |
| $GGL_{\text{Linear},AB}$ | | | | | -0.006** | |
| | | | | | (0.003) | |
| $GGL_{\text{Linear},AB}$ | | | | | 0.035*** | |
| $\times$ $complexity_r$ | | | | | (0.012) | |
| $GGL_{\text{Convex},AB}$ | | | | | | -0.118*** |
| | | | | | | (0.043) |
| $GGL_{\text{Convex},AB}$ | | | | | | 0.571*** |
| $\times$ $complexity_r$ | | | | | | (0.195) |
| $complexity_r$ | 4.833*** | 6.701*** | 6.437*** | 4.752*** | 3.711*** | 4.696*** |
| | (0.829) | (0.921) | (0.934) | (0.922) | (0.968) | (0.851) |
| $CD_{AB}$ | 0.963*** | 0.947*** | 0.938*** | 0.935** | 0.952*** | 0.923** |
| | (0.365) | (0.354) | (0.360) | (0.368) | (0.368) | (0.372) |
| $InstOwn_B$ | -0.116 | -0.166 | -0.211 | -0.140 | -0.070 | 0.042 |
| | (0.315) | (0.301) | (0.290) | (0.283) | (0.292) | (0.302) |
| $d_{B,r}$ | -2.033*** | -2.053*** | -2.054*** | -2.020*** | -2.006*** | -2.035*** |
| | (0.281) | (0.281) | (0.283) | (0.285) | (0.283) | (0.287) |
| $Pstock_B$ | 0.260*** | 0.267*** | 0.267*** | 0.261*** | 0.259*** | 0.266*** |
| | (0.037) | (0.038) | (0.038) | (0.038) | (0.037) | (0.038) |
| Controls | YES | YES | YES | YES | YES | YES |
| Deal-FE | YES | YES | YES | YES | YES | YES |
| Observations | 13973 | 13973 | 13973 | 13973 | 13973 | 13973 |
| $Pseudo-R^2$ | 0.278 | 0.274 | 0.280 | 0.283 | 0.284 | 0.273 |

*Note:* This table reports coefficient estimates for the different common ownership measures and their interaction with the variable $complexity_r$ from the probit model in equation (8) using the entire sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to 1 for the dyads $AB$ that engage in the transfer of the reassignment $r$ and 0 for the control pairs. The variable $complexity_r$ measures the inverse of the concentration of the reassigned patents in IPC 2-digit patent classes. All specifications include deal-group fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.