Universitat Autònoma de Barcelona

Essays in Corporate Finance and Innovation

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Introduction

Investments in innovation create new technological know-how, which is the primary cause of economic growth. Furthermore, this innovative know-how contributes the most to economic growth as it is disseminated and allocated to its most efficient uses in the economic system. Moreover, significant technological innovations not only enlarge the economic possibilities but also impact societies on a larger scale; they influence the allocation of productive factors causing the rise and decline of firms and whole sectors of the economy and thereby affecting firms' and workers' choices and livelihoods.

For these reasons, it is critical to understand the determinants of investment in and the dissemination of innovation and its consequences for the economy and the broader society. In this thesis, I contribute to our understanding of these determinants and consequences. First, I study the heterogeneous influence of different institutional owners on firms' innovation strategies and output (Chapter 1). Second, I analyze how common ownership by institutional investors influences firm matching in the market for technology, impacting the reallocation of innovative know-how (Chapter 2). Third, I investigate the effect of automation on the sectoral reallocation of labor and capital in the economy (Chapter 3).

In Chapter 1, *Does Institutional Ownership Composition matter for Corporate Innovation?* written with Bing Guo, David Pérez-Castrillo, and Anna Toldrà-Simats, we investigate the heterogeneous impact of institutional investors on the firms' strategic choices regarding investments in innovation and their innovative output. Institutional investors vary greatly in their involvement in firm decisions. Whereas some institutional investors have incentives to monitor and influence firms in a firm-specific manner actively, others rely on standard measures or the uniform recommendations of proxy advisors like the ISS. We study the heterogeneous effects of different institutional owners on firms' innovation strategies and outcomes. We find that institutional investors with monitoring incentives lead firms to acquire innovation from external sources. In contrast, non-motivated blockholder investors induce firms to invest in innovation primarily by developing their internal R&D. Both motivated owners and blockholders have a positive effect on patents and citations relative to other institutional investors. Still, the impact of motivated investors is 2.5 times larger than that of blockholders. The mechanisms behind these effects are different. Whereas motivated investors encourage innovation because they reduce managerial career concerns, blockholders do so by improving firms' corporate governance. These results shed light on the importance of active monitor funds to help firms achieve value-maximizing outcomes.

In Chapter 2, *Common Ownership and the Market for Technology*, I study the effect of institutional investors' common ownership on technology transfer between publicly traded companies. In my theoretical model, a technology provider can sell a technology to potential buyers. A technology transfer consists of trading patents and the transmission of unverifiable know-how which is not codified in the patents that are traded. Common owners maximize their portfolio value and, thus, incentivize firms' managers to internalize other firms' profits. I show that common ownership alleviates the moral hazard problem of know-how transmission. Hence, common ownership between the technology provider and a particular firm positively affects the probability of transferring the technology to this firm since the incentives induced by common ownership increase the value of a potential deal by improving the quality of the know-how transfer. In my empirical analysis, I use USPTO patent reassignment data, and I provide evidence for this positive effect of common ownership. Notably, the impact of common ownership on the adopter selection is stronger for deals that involve more complex technologies, for which the transmission of know-how is likely to be essential. I apply different matching techniques and an instrumental variable strategy based on the trading partners' pairwise stock market index membership to account for potential endogeneity. My results suggest that the alleviation of moral hazard in know-how transfer is a plausible mechanism through which common ownership facilitates technology transfer, increases the quality of know-how transmission, and, therefore, affects the reallocation of innovative knowledge.

In Chapter 3, *Automation and Sectoral Reallocation*, written with Tommaso Santini and Eugenia Vella, we study the effects of the adoption of robots in the manufacturing sector in Germany by calibrating a search and matching model. Empirical evidence in Dauth et al. (2021) suggests that industrial robot adoption in Germany has led to a sectoral reallocation of employment from manufacturing to services, leaving total employment unaffected. We rationalize this evidence through the lens of a general equilibrium model with two sectors, matching frictions, and endogenous participation. Automation induces firms to create fewer vacancies and job seekers to search less in the automatable sector (manufacturing). The service sector expands due to the sectoral complementarity in the production of the final good and a positive wealth effect for the household. Analysis across steady states shows that the increase in service employment can offset the reduction in manufacturing employment. The model can also replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany between 1994 and 2014.

Chapter 1

Does Institutional Ownership Composition matter for Corporate Innovation?

1.1 Introduction

Innovation and technological progress are the most important sources of economic growth and development.[1] Publicly traded companies have an advantage with respect to private firms when investing in risky innovation because they can spread risk across a large mass of investors (Aghion et al., 2013). However, free-riding problems in widely-held companies (Grossman and Hart, 1980), together with asymmetric information and agency costs, may lead managers to invest in innovation inefficiently.[2]

The presence of large shareholders in public companies has been recognized as a possible solution to the free-rider problems and agency conflicts (Shleifer and Vishny, 1986). Several empirical studies analyze how institutional owners influence important corporate decisions such as acquisitions (Fich et al., 2015), corporate governance (Pederson, 2014), or innovation (Aghion et al., 2013). The majority of these studies assumes that the various institutional owners have homogeneous preferences regarding corporate strategy and therefore influence firm decisions in the same way. However, it is well known that institutional owners are vastly heterogeneous along several dimensions. Recent studies point out that institutional investors vary greatly in their approach to monitoring and voting upon firm policies (Iliev and Lowry, 2015; Corum et al., 2021). Specifically, these authors suggest

[1] Schumpeter (1911), Arrow (1962), Grossman and Helpman (1991), Aghion and Howitt (1992).

[2] Examples of these problems are the career concerns of risk-averse managers that fear being fired if a research project fails (Kaplan and Minton, 2006; Aghion et al., 2013), the obligation to publish quarterly results (Porter, 1992), or the pressure to meet the earnings forecasts periodically issued by financial analysts (Stein, 1988; He and Tian, 2013; Guo et al., 2019).

that while some investors actively assess and evaluate the issues up for vote, others dedicate less effort or rely entirely on proxy advisory services companies such as the Institutional Shareholders Services (ISS). If proxy advisor recommendations are as good as those that investors would obtain by getting actively involved, then we should not find any differences in corporate policy despite firms having heterogeneous institutional ownership. However, proxy advisors like the ISS are often criticized for issuing "blanket recommendations." In other words, they recommend investors to vote for or against specific governance or policy issues uniformly in all firms. If firm-specific voting leads to superior outcomes than a "one-size-fits-all" approach, then we should observe differential results on firms.

Despite the increasing literature about institutional owners' heterogeneous involvement in firms, the number of studies that explore their possible differential effects on corporate policy and performance is still small. The focus of this paper is to assess the differential effects of heterogeneous institutional investors on firm innovation. This question is very relevant because, for instance, institutional investors already accounted for close to 70% of the US stock market by 2010 (Blume et al., 2014). Moreover, the reliance of institutional investors on proxy advisory services has been increasing in recent years, raising concerns about the repercussions of their recommendations (Iliev and Lowry, 2015).[3,4]

We define two types of institutional shareholders based on the relative size of their stock holdings. We argue that, depending on how institutional investors allocate their funds' money to portfolio companies, they will have different incentives to monitor and a different influence on corporate innovation. First, following the literature, we define the *motivated monitors* in a given company as those institutional shareholders for whom the value of their holding in that company is in the top 10% of their portfolio (Fich et al., 2015). Second, we define the *blockholders* as those institutional shareholders with more than 5% ownership in a given company. Therefore, a blockholder is a prominent investor from the company's point of view, whereas the company is a large investment from a motivated investor's point of view. We compute the percentage ownership of these types of investors in a company relative to total institutional ownership.

Since we are interested in studying the influence of these types of investors on firm innovation, we use three different measures to capture the various channels companies can use to invest in innovation. The first measure is firms' spending in Research and Development (R&D), which allows firms to produce innovation internally by exploiting the firm's resources. The second channel is firms' acquisitions of other innovative firms,

[3] According to Iliev and Lowry (2015), over 25% of mutual funds rely almost entirely on ISS recommendations.

[4] A few papers have studied the effect of different types of institutional owners on corporate behavior by focusing on another important dimension in which institutional owners differ, which is their investment horizon. These papers consistently find that the negative effects of short-term pressure on corporate behavior are attenuated with increases in the presence of long-term investors (Bushee, 1998; Gaspar et al., 2005; Chen et al., 2015; Derrien et al., 2013; Samila et al., 2021). We differ from these papers because we focus on institutional owners' degree of involvement in corporate decisions depending on size of their investment rather than on their indirect effects due to their trading strategy.

enabling them to acquire external innovation developed by other companies. The third measure is firms' investment in corporate venture capital (CVC), which allows firms to keep updated about the most recent innovations in the sector. Then, they can use that knowledge to either develop similar products internally or acquire the start-ups where they invested. To measure innovation output, we use firms' future number of patents and citations.

We argue that firms will use different channels to invest in innovation, affecting their final innovation outcome, depending on the proportion of institutional ownership in the hands of motivated monitors or blockholders. Here is why. Let us suppose that investors first decide whether to acquire information to monitor companies' doings and then decide on how to influence companies' decisions based on that information. Under the assumption that acquiring information to monitor managers is costly, only those investors for whom a firm represents a large holding in their portfolio will have an incentive to collect such information from that firm. Indeed, just as firms are more likely to focus on their more valuable projects, institutional investors might have more incentives to monitor and get more involved in those firms to which they allocate more resources. The reason is that the benefits from monitoring only outweigh the cost of information acquisition if the stock holding represents a large enough value in the institution's portfolio. Hence, we expect *motivated monitors* to monitor firms actively. In contrast, we do not expect *blockholders* to watch a particular firm more than another, even if those investors might hold large blocks in some firms, as long as these firms represent a small part of the institution's total portfolio.[5]

After the information acquisition decision, investors will use their voice to influence firm choices to the best of their knowledge. According to our previous arguments, motivated monitors will have superior information than blockholders. Thus, they might use this information to influence corporate decisions that affect innovation.[6] Managers, anticipating motivated investors' monitoring efforts, will have incentives to propose value-increasing investments in innovation. In equilibrium, the presence of motivated owners should increase the likelihood that firms invest in valuable R&D projects, innovative acquisitions, and CVC.

[5]Iliev and Lowry (2015) also point out that whether a fund is an active or a passive voting fund depends on the costs and benefits associated with each strategy, i.e., the cost of acquiring information and the benefit of active engagement, which may vary across funds. Schmidt and Fahlenbrach (2017) find that passive ownership is associated with worse governance, whereas a close paper by Appel et al. (2016) finds that passive ownership is related to better governance. Schmidt and Fahlenbrach (2017) reconcile these findings by pointing out that whether governance improves or worsens depends on the relative costs of monitoring the specific proposals. In particular, some activities such as board appointments or mergers and acquisitions are much more costly to monitor for low-cost, low-overhead institutions than basic corporate governance characteristics. Therefore, such institutions might focus more on basic governance while passing on more complex issues.

[6]Note that even if motivated investors do not have large enough ownership stakes to influence firms' decisions on their own, they can share the acquired information with other investors to align their votes. Motivated investors not only have stronger incentives to obtain information, but these stronger incentives make it easier for them to convince other shareholders to trust their informed recommendations.

Their overall effect on patents and citations should be positive and significant.

In contrast, as we argued above, blockholders that are not motivated monitors have fewer incentives to acquire costly information because their stock holdings do not represent an essential part of their portfolios. Then, expecting no monitoring from blockholders, entrenched managers might have an incentive to propose privately beneficial but possibly value-destroying investments. Anticipating such behavior from managers, blockholders will have pessimistic beliefs about the type of investments that managers submit and will tend to vote against them. Our hypothesis is that firms with more blockholders will be less likely to undertake investments, such as mergers and acquisitions, which require collecting costly information and voting consent. Hence, we expect firms with more blockholders to make less innovative acquisitions.

However, their effect on other innovation decisions that do not require voting consent, such as R&D investment and CVC, is less clear. On the one hand, blockholders may have no impact on these decisions because they do not monitor them directly; on the other hand, they may affect them through mechanisms that do not require a high monitoring cost. For instance, blockholders may improve firms' corporate governance by consistently voting on basic governance issues according to a pre-defined program or relying on proxy advisor firms like the ISS. Our hypothesis is that blockholders are more likely to influence firms using their votes to affect standard governance practices and that if blockholders have any (positive) effect on R&D and CVC investments, it will be indirectly via improvements in firms' corporate governance.

We test the above hypotheses taking into account the potential endogenous nature of a company's shareholder composition. Indeed, firms' institutional investor heterogeneity may depend on firm characteristics that also determine firms' capacity to innovate. To establish causality, we follow the previous literature (Fich et al., 2015; Appel et al., 2016; Crane et al., 2016; Schmidt and Fahlenbrach, 2017) and use an instrumental variables approach where we exploit the composition and reconstitutions of the Russell 1000 and the Russell 2000 indexes as a source of exogenous variation for the heterogeneity of firms' institutional ownership.

Our tests results indicate that an increase in the ownership by motivated investors relative to total institutional ownership increases the probability that firms acquire other companies for innovation purposes and invest in CVC. However, motivated investors seem to not affect firms' investments in internal R&D. In contrast, we find that firms with higher blockholder ownership relative to other institutional investors' ownership are less likely to acquire other firms. These investors do not induce firms to acquire more innovative targets either, nor to invest in CVC. However, the effect of blockholder ownership on R&D investments is positive and highly significant. Overall, these results suggest that while both types of investors have a positive impact on some innovation inputs, motivated investors increase the innovation production that comes from external sources, i.e., acquisitions; whereas firms with more blockholders produce innovation that comes mainly from internal R&D.

This is important because, as some papers suggest,[7] acquiring innovation from external sources might stimulate innovation production further and enable firms to produce more efficient innovations than when investing only in internal R&D.

We test the effect of the composition of institutional ownership on firms' innovation output. We find that both types of investors positively and significantly impact firms' future patents and citations. Interestingly, the positive effect of motivated investors on innovation output is economically and significantly larger than that of blockholders. Specifically, for the average company, i.e., with 30 patents and 343 citations, a 1 percentage point increase in the ownership by motivated investors relative to total institutional ownership increases the company's number of patents by 0.69 (an increase of 2.3%) and its citations by about 7 (an increase of 2.03%). In contrast, for the same average company, a 1 percentage point increase in ownership by blockholders increases the firm's patents by 0.26 (an increase of 0.9%), and it increases its citations by 2 (an increase of 0.6%). Hence, firms with motivated investors produce about 2.5 times more patents and about 3.5 times more citations than those with blockholders, and these differences are significant. Our results align with the previously mentioned papers since we find that innovation output is larger in firms with more motivated investors, who encourage external innovation.

We then explore the mechanisms behind the effects of motivated and blockholder ownership on firm innovation. As we argued above, we hypothesize that motivated investors are more likely to influence innovation through their monitoring role. In contrast, blockholders are more likely to affect innovation indirectly via improving firms' corporate governance. To distinguish between these two mechanisms, we test the Aghion et al. (2013) model's predictions. These authors argue that in a career concern model (Holmström, 1999), increased monitoring may increase managerial incentives to innovate because it protects managers against bad outcomes (i.e., career risks) due to bad luck. And in a model where managers prefer a quiet life (Hart, 1983; Bertrand and Mullainathan, 2003), institutional investors may induce managers to innovate through better corporate governance. According to Aghion et al. (2013), the previous two mechanisms can be distinguished empirically because they lead to opposite predictions on the interaction between institutional ownership and competition. We test the model's predictions and find support for motivated investors' monitoring role and blockholders' governance role.

Finally, we provide further support for the distinction between the monitoring role of motivated investors and the governance role of blockholders with an additional test. We argue that innovative acquisitions are more likely to occur in the presence of motivated investors because these investors have incentives to acquire costly information and use it to monitor managers. Hence, having access to firm information is crucial for motivated investors. We hypothesize that if motivated investors monitor managers and acquire information to do so, their monitoring task will be made easier when more information about firms is available. Hence, motivated investors and financial analysts should be complements

[7] Chesbrough (2003); Almirall and Casadesus-Masanell (2010); Guo et al. (2019).

in fostering firm innovation.[8] In contrast, as we discuss above, blockholder investors' effect on innovation does not occur through an information channel but improved firm governance. Since financial analysts are often viewed as an external governance mechanism (Chen et al., 2015), we expect blockholders and financial analysts to be substitutes in increasing firm innovation. Our tests provide support for our hypotheses.

Overall, we contribute to the literature by shedding some light on the heterogeneous incentives of institutional owners and their distinct effects on firms. More specifically, while both motivated investors and blockholders positively affect innovation relative to other institutional investors, active monitoring leads firms to innovate more. Moreover, the mechanisms behind these effects are different.

The rest of this paper is organized as follows. Section 1.2 discusses the related literature and our contributions. Section 1.3 presents the data and the variables. Sections 1.4 and 1.5 present the empirical strategy and the baseline results. Section 1.6 provides the test of the Aghion et al. (2013) models. Section 1.7 studies the complementarity between institutional ownership and financial analysts. Section 1.8 concludes.

1.2 Related Literature

Our paper relates to several strands of literature. The first is the literature investigating the effect of large shareholders on corporate decisions, governance, and performance (Shleifer and Vishny, 1986; Cronqvist and Fahlenbrach, 2008; Grennan et al., 2017; Harford et al., 2018). Some empirical papers in this strand focus on the effect of passive institutional investors, i.e., index trackers (Schmidt and Fahlenbrach, 2017; Appel et al., 2016; Crane et al., 2016; Boone and White, 2015); while others focus on the role of activists (Aghion et al., 2013; Brav et al., 2008; Fich et al., 2015). Schmidt and Fahlenbrach (2017) find that exogenous increases in passive ownership lead to increases in CEO power and decreases in new independent director appointments, both at the detriment of firm value. In contrast, Appel et al. (2016) find that an increase in passive ownership results in better governance, i.e., more equal voting rights and the removal of takeover defenses, which leads to better long-term firm performance. Other authors also find that quasi-indexers improve firm governance through voting (Crane et al., 2016) and encourage information disclosure (Boone and White, 2015). The closest paper to ours is Aghion et al. (2013), which examines the impact of institutional ownership on innovation. It provides evidence that institutional owners increase innovation because, by monitoring managers, they alleviate managerial career concerns. Another related paper by Fich et al. (2015) studies the effect of motivated investors on the gains of takeover targets by including the effect of blockholders as a control variable. Overall, these papers focus on institutional investors

[8]The recent paper by Guo et al. (2019) shows that financial analysts have a positive effect on innovation because they reduce information asymmetries by spreading information about firms in analyst reports, recommendations, or press releases.

that are either passive or activists. However, they fail to include both types of investors in the same empirical framework to study their differential causal effects.

A related paper by Bushee (1998) classifies institutional owners in three groups according to their trading strategy and includes them in the same empirical analysis to study their heterogeneous effects. The author finds that investors with high turnover and momentum trading encourage myopic investment behavior, which negatively affects R&D. In contrast, more long-term oriented institutions reduce myopic behavior, which increases R&D. We distinguish from this paper by considering several innovation channels rather than only studying investment in R&D, which allows us to have a better idea of firms' innovation strategy as a whole. Besides, we classify investors based on the relative size of their ownership rather than their trading strategy, which allows us to understand better their incentives to monitor managerial decisions and the mechanisms behind their influence on firm innovation.

Second, our paper relates to the literature that studies the different incentives of institutional owners to monitor managers actively and their resulting voting behavior (Iliev and Lowry, 2015; Brav et al., 2008; Heath et al., 2022; Malenko and Malenko, 2019; Corum et al., 2021). These papers try to understand which investors are more likely to monitor firms actively and which ones tend to rely more on proxy advisor recommendations. Among these papers, only Heath et al. (2022) includes some analysis that compares the effect of active monitors relative to index funds on firm corporate governance. Our paper contributes to this literature first by studying the different monitoring incentives of institutional owners in the context of innovation and second by integrating different types of institutional owners in a unified framework to provide evidence of their heterogeneous effects. We also uncover two distinct mechanisms behind these effects: due to the relative size of their holdings, motivated investors encourage firm innovation by actively monitoring firms, and blockholder investors encourage firm innovation by improving corporate governance.

Finally, our work is related to the papers that use the Russell 1000/2000 index reconstitutions as an exogenous shock to institutional ownership (Fich et al., 2015; Appel et al., 2016; Schmidt and Fahlenbrach, 2017). We modify the previous papers' empirical strategy because we use this exogenous shock to separately instrument each of our two variables that measure motivated institutional ownership and non-motivated blocks since both variables are presumably endogenous. By instrumenting each variable separately, we allow for the effect of the Russell 1000/2000 index reconstitutions to be different. Indeed, we argue that it is possible that when index-tracking companies are forced to change their holdings in some stocks due to index reconstitutions, the relative ownership by other types of owners may vary (see footnote 18).

1.3 Data

1.3.1 Sample selection and data sources

We construct our sample based on information of US public firms for the period 1990 to 2012.[9] We start by retrieving financial information for all the companies in Compustat during our sample period, excluding financial and utilities firms (standard industrial classification (SIC) codes between 4000 and 4999, and between 6000 and 6999). Then, we merge this data with information from several other databases as we detail in what follows.

We use the Thomson Reuters Institutional Holdings 13F database (file s34) to obtain institutional ownership information to construct our main explanatory variables. For the September quarter between 1990 and 2012, we collect information concerning the number of outstanding shares, the share prices, and the shares held by institutional investors in a given firm. File s34 of form 13F suffers from several data quality problems. Therefore, we manually clean the data from duplicate observations, incorrectly assigned holdings information, and replace the missing information. Specifically, we supplement the information with data from the Center for Research in Security Prices (CRSP) for missing values on the end-of-quarter stock price and outstanding shares. After cleaning the data, we aggregate fund holdings at the institutional investor level.[10]

For institutional holdings, we take the quarter that ends in September because we instrument institutional ownership with variables that come from the Russell index composition and annual reconstitutions, which happen in June. Thus, we expect the Russell index reconstitutions to cause institutional ownership changes mainly in the second semester of the year. Since institutional ownership data is only available quarterly, we choose the first available quarter in which reconstitutions can have an effect.[11] We gather data on the index constituents of the Russell 1000 and Russell 2000 indexes and their ranking within the indexes from the FTSE Russell database. We merge the index constituents with the previous datasets, and we only keep those observations that merge. Hence, our sample is restricted to those stocks present in the Russell 1000 and 2000 indexes between 1990 and 2012.

In addition to R&D expenses obtained from Compustat, we collect data to construct two additional measures of firms' innovation strategy following Guo et al. (2019). We get acquisitions information from the Securities Data Company (SDC) Mergers and Acquisitions database. And we obtain data regarding firms' investments in Corporate Venture Capital (CVC) from the Thomson One Private Equity database. Even though Thomson One provides CVC funds' parent companies' identity, we manually check for potential mistakes and correct them using Google and LexisNexis.

[9] We intentionally pick this sample period to study a period of years that is consistent with our patents and citations data, which spans from the year 1990 to 2010.

[10] Some large institutional investors such as BlackRock report their holdings further disaggregated at the asset manager level. We take this into account and aggregate this information when necessary.

[11] We also replicate the regressions using the December quarter, and the results are very similar.

Additionally, we collect patent and citation information to construct several measures of firms' innovation output. We obtain data from 1990 to 2006 from the National Bureau of Economic Research (NBER) Patent Citation database (Hall, Jaffe, and Trajtenberg, 2001). We extend the patent and citation data using the Harvard Business School (HBS) patent database, which includes patents granted and citations until 2010. We mitigate truncation problems by excluding observations after 2006 in the regressions that require patent or citation information. Following Hall et al. (2001) and Atanassov (2013), we also scale the raw number of citations (patents) by the average number of citations (patents) in the same technology class in the same year to further address truncation.[12]

We obtain financial analyst information from the Institutional Brokers Estimate Systems (I/B/E/S) database to construct a measure of analyst coverage used as a control in our regressions. Finally, we create a variable, Flow-to-Stock, that we include in a Heckman selection model (Heckman, 1979) in section 1.5.2. To construct this variable, we obtain mutual funds holdings data from CDA Spectrum/Thomson and mutual fund flow as well as individual stock return data from CRSP.

When we merge all the aforementioned information, we obtain a final sample of 19,801 firm-year observations and 2,454 firms from 1990 to 2012. We use this sample to estimate all our regressions.

1.3.2 Variable construction

Main independent variables

Our main independent variables are two measures of institutional ownership. The first measure, which we call *MotivatedOwn*, is the total share of ownership of motivated owners in a given firm and year relative to the total ownership by institutional investors in that firm and year. Following Fich et al. (2015), we define motivated owners as those institutional investors for whom the holding value of the company's shares is in the top 10% of the institution's portfolio as of September 30th each year. The second measure, which we call *BlockOwn*, is the total share of ownership of blockholders relative to institutional ownership. We define blockholders as those institutional investors holding at least 5% of the company's outstanding shares as of September 30th each year. For example, a firm with 25% total institutional ownership, with one motivated investor with 4% ownership and two blockholders that each has 5% and 6% ownership, would have a *MotivatedOwn* of 16% and a *BlockOwn* of 44%.[13]

To distinguish the possibly different effects of these two types of investors, we do not

[12]For more details on innovation data, see Guo et al. (2019).

[13]The literature establishes that small investors such as retail investors barely influence company decisions due to free-riding problems (Shleifer and Vishny, 1986) and lack of power. Thus, we construct measures to classify types of institutional owners relative to total ownership of institutional investors instead of using merely investors' percentage ownership. However, we find similar results when we do our analysis using non-relative measures of ownership.

classify in either category those investors that are at the same time blockholders and motivated monitors. Instead, we include these investors as 'other' institutional owners. These "disjoint" measures allow us to identify how each kind of investor influences firm innovation.[14]

Dependent variables

Our main dependent variables are measures of firms' innovation strategy and outcomes. We consider three different channels to capture different ways in which firms can invest in innovation. First, firms can invest in internal R&D. They may either increase R&D expenses to increase in-house innovation production or cut R&D to decrease innovation expenses. To capture these effects, we construct two variables: *R&DChange* is the difference between current and previous year's R&D (scaled by total assets), and *R&DCut* is an indicator variable which takes the value one if R&D expenses (scaled by total assets) in the current year are smaller than in the previous year, and equals zero otherwise.

Second, acquisitions of other firms can be a source of know-how, patents, and other innovative assets. We measure firms' acquisition activity with two different variables: the dummy variable *Acquisition* takes the value one if a firm acquires one or more companies in a specific year and equals zero otherwise; *LnAcquisitions* is the natural logarithm of (one plus) the total number of acquired companies in a given year.

To better assess whether acquisitions are a way for firms to invest in innovation, we use two variables that are proxies for the acquired firms' innovativeness. *LnTargPatent* corresponds to the natural logarithm of (one plus) the cumulative number of patents on average of all target firms, and *LnTargCite* is analogously computed as the natural logarithm of (one plus) the cumulative number of citations on average of all target firms. Both measures capture the average innovation stock of target companies and are adjusted for truncation, as explained in the previous section.

Third, firms can invest in start-ups via their Corporate Venture Capital (CVC) funds to learn about the most recent innovations, in addition to earning financial returns. To measure firms' investments in CVC, we construct the variable *CVC investment*, a dummy equal to one each year a firm's CVC fund invests in start-ups and zero otherwise.

We measure firms' innovation output based on their patents and citations. The variable *LnPatents* is the natural logarithm of (one plus) the number of applied and eventually granted patents each year. The variable *LnCitations* corresponds to the natural logarithm

[14] Out of the total institutional ownership in the average firm in our sample, which corresponds to 65%, investors that are at the same time blockholders and motivated monitors hold about 6.95% ownership. We first included these investors as a separate category in our regressions, but the results for this category were generally not significant. Hence, we decided to include them in the category with the rest of the institutional investors. Also, we replicate all our regressions using the variables of motivated monitors and blockholders without excluding from these variables the investors that are at the same time motivated and blockholders (i.e., non-disjoint). Our results are qualitatively and quantitatively very similar to our main results.

of (one plus) the number of firms' citations each year. Both variables are adjusted for truncation problems, as explained in the previous section.

Control variables

Following the literature, we control for several firm and industry characteristics. We include *InstOwn* as a measure of total institutional ownership (i.e., the share of stocks held by all 13F institutions on September 30th each year). This measure is adjusted in those cases where the ownership by 13F institutions adds up to a value larger than one (for example, due to short selling) by downscaling each institutional investor's ownership.[15]

As shown previously in the literature, financial analyst coverage significantly affects firms' innovation strategies (Guo et al., 2019) and outcomes (He and Tian, 2013; Guo et al., 2019). Therefore, we include the variable *LnCoverage*, which is the natural logarithm of (one plus) the number of analysts, measured as the mean of the 12 monthly numbers of earnings forecasts that a firm receives annually, from the I/B/E/S summary file.

The rest of the control variables are *FirmSize*, which is the natural logarithm of total assets; *R&D*, which corresponds to R&D expenses scaled by total assets; *FirmAge*, which is the number of years a firm has existed in Compustat; *Leverage*, which is the ratio of firm debt to total assets; *Cash*, which corresponds to firms' cash scaled by total assets; *Profitability*, which is the return on equity (ROE); *PPE*, which is computed as firms' property, plant, and equipment (PPE) scaled by total assets; *Capex*, which corresponds to firms' capital expenditures scaled by total assets; *MarketCap*, which measures firm's market capitalization at the fiscal year end; and the *KZ* index which is a measure of financial constraints (Kaplan and Zingales, 1997). We also include an index of corporate governance, *CGIndex*, following an approach similar to the one in Bertrand and Mullainathan (2001). To capture industry concentration, we include the variable *HHI*, which is the Hirschman–Herfindahl index based on market shares, and its square, HHI^2. To mitigate the effect of outliers, we winsorize *Profitability* and the *KZIndex* at the 1st and 99th percentiles.

Instrumental variables

As we explain in Section 4, endogeneity might be a concern in our regressions. To address endogeneity, we use the composition and annual reconstitutions of the Russell 1000 and the Russell 2000 indexes as a source of exogenous variation that causes changes in institutional ownership (Chang et al., 2015; Appel et al., 2016; Fich et al., 2015; Schmidt and Fahlenbrach, 2015).

We instrument both our measures of motivated institutional owners and blockholders as both are potentially endogenous in our setting. We follow the approach by Schmidt and Fahlenbrach (2017) and include three instrumental variables related to the reconstitutions of the Russell 1000 and 2000 indexes in the first-stage regression. First, the dummy variable

[15] We obtain very similar results if we exclude *InstOwn* as a control variable in our regressions.

Table 1.1: Variable Definitions

Variables	Definitions
Independent variables	
InstOwn	Percentage of firm's outstanding shares held by 13F institutions (Thomson Reuters s34 file)
MotivatedOwn	Percentage of outstanding shares held by (non-blockholder) motivated monitors divided by *InstOwn*
BlockOwn	Percentage of firm's outstanding shares held by (non-motivated) blockholders divided by *InstOwn*
Dependent variables	
R&DChange	Ratio of R&D expenses (Compustat data item ♯46) to total assets (♯6) at t minus ratio of R&D expenses to total assets at $t-1$
R&DCut	Indicator variable equal to one if R&D (♯46)—scaled by total assets (♯6)—at t is lower than that at $t-1$, and zero otherwise
Acquisition	Indicator variable equal to one when a firm acquires one or more other companies, and zero otherwise
LnAcquisitions	Natural logarithm of (one plus) the number of target companies acquired
LnTargPatent	Natural logarithm of (one plus) the accumulated number of patents on average of all target firms acquired
LnTargCite	Natural logarithm of (one plus) the accumulated number of citations on average of all target firms acquired
CVC investments	Indicator variable equal to one for each year in which a firm invests in a start-up, and zero otherwise
LnPatents	Natural logarithm of (one plus) the number of granted patents per year of a firm
LnCitations	Natural logarithm of (one plus) the number of citations per year of a firm
Control variables	
LnCoverage	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
R&D	R&D expenses (♯46) divided by book value of total assets (♯6)
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)
Cash	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)
PPE	Property, plant, and equipment (♯8) divided by book value of total assets (♯6)
Capex	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 calculated as sum of sales revenue scaled by sales of four-digit standard industrial classification (SIC) code
HHI^2	Squared Herfindahl-Hirschman Index
Instruments	
Russell1000to2000	Indicator variable equal to one if a firm was member of the Russell 1000 index in the preceding year and is member of the Russell 2000 index in the current year, and zero otherwise.
Russell2000to1000	Indicator variable equal to one if a firm was member of the Russell 2000 index in the preceding year and is member of the Russell 1000 index in the current year, and zero otherwise.
RankChange	Change in the Russell index rank compared to the previous year ($rank_t - rank_{t-1}$) divided by 100.
Flow-to-Stock	The relative mutual fund outflow pressure due to large investor redemption on each stock as a percentage of the stock owned by each fund.

Russell1000to2000 takes the value one if a firm was a member of the Russell 1000 index in the preceding year ($t-1$) and is a member of the Russell 2000 index in the current year (t), and zero otherwise. Second, the variable *Russell2000to1000*, which is a dummy variable that takes the value one if the firm was part of the Russell 2000 Index at $t-1$ and switches to the Russell 1000 index at t. And third, the variable *RankChange* which is a continuous variable that measures the change in firms' rank within the indexes compared to the firm's previous year's rank ($rank_t - rank_{t-1}$) divided by 100. The rank of a firm along the two indexes is based on firms' raw market capitalization. A more detailed explanation of the instruments and empirical strategy is provided in section 1.4. All variable definitions are summarized in Table 1.1.

1.3.3 Summary Statistics

Table 1.2 provides summary statistics of the variables used in our analysis. Regarding our main independent variables, institutional investors (*InstOwn*) own 65% of the outstanding shares in the average firm in our sample, motivated monitors own 10.7% of the total outstanding shares in the average firm, and their ownership relative to total institutional ownership (*MotivatedOwn*) is about 15.7%. All non-monitoring Blockholders in a firm own together 11.2% of outstanding shares on average, and their resulting ownership relative to total institutional ownership (*BlockOwn*) in the average firm is 16.1%. Regarding the dependent variables, the average firm in our sample invests about 6.7% of their assets in R&D, and the average R&DChange is less than 0.5%. Moreover, 49.1% of the firms in our sample cut R&D relative to assets during the sample period. Regarding acquisitions, about 20.9% of firms are engaged in acquisitions in a given year, and the average number of acquired targets is 0.285, including those firms that do not acquire any target. Conditional on acquiring, the average firm acquires 1.37 target firms. In our sample, 2,966 firm-year observations are involved in acquisitions by 2006.[16] Acquired firms have on average about 18 patents and 277 citations. When we consider all the firms in our sample, the number of firms' patents and citations is 31 and 343, respectively, suggesting that acquired firms are a bit smaller or younger in terms of innovation. Only a small portion of firms in our sample invest in start-ups. Specifically, the probability that a given company in our sample invests in CVC in a given year is 2.2%.

Since firms in our sample are all in the Russell 1000 and 2000 indexes, they are pretty large, mature, and get analyst attention. Around 9 financial analysts follow the average firm in our sample, it has about $4.8 billion in total assets, and it is around 23 years old. The mean leverage ratio of these firms is 18.4%, and their ratio of cash to assets is 21.1%. Firms' profitability, measured by the return on equity, is 25.7%, the ratio of tangible assets

[16] We consider acquisitions only up until 2006 to be consistent with our sample period for patents and citations. Even if we calculate firms' patents and citations using data until 2010, following the literature, we omit observations after 2006 in all our regressions involving patents and citations to avoid truncation problems.

Table 1.2: **Summary Statistics.** This table reports the descriptive statistics for the variables of our main regressions based on the sample of US public firms from 1990 to 2012.

Variable	25th percentile	Median	Mean	75th percentile	Std. Dev.	No. of Obs.
Independent variables						
InstOwn	0.489	0.687	0.650	0.842	0.244	19,801
MotivatedOwn	0.000	0.077	0.157	0.210	0.208	19,801
MotivatedOwn (abs.)+	0.000	0.048	0.107	0.149	0.141	19,801
BlockOwn	0.000	0.130	0.161	0.268	0.165	19,801
BlockOwn (abs.)+	0.000	0.074	0.112	0.183	0.122	19,801
Dependent variables						
R&D	0.006	0.032	0.067	0.093	0.099	19,801
R&DChange	-0.005	0.000	0.000	0.005	0.049	15,904
R&DCut	0.000	0.000	0.491	1.000	0.500	15,904
Acquisition	0.000	0.000	0.209	0.000	0.406	19,801
NumofAcquisitions	0.000	0.000	0.285	0.000	0.680	19,801
NumofTargPatent	0.000	0.000	17.817	4.000	153.216	2,966
NumofTargCite	0.000	0.000	276.836	58.000	2061.819	2,966
Patents	0.000	1.000	30.525	10.000	163.105	12,601
Citations	0.000	3.000	342.630	78.000	2234.828	12,601
CVC investments	0.000	0.000	0.022	0.000	0.147	19,801
Controls						
Coverage	4.000	7.417	9.472	13.167	7.479	19,801
FirmSize (in M)	278.954	735.334	4,765.948	2,293.1	24,870.28	19,801
FirmSize (ln)	5.631	6.600	6.777	7.738	1.605	19,801
FirmAge (in years)	10	17	22.735	34	15.897	19,801
FirmAge (ln)	2.303	2.833	2.866	3.526	0.741	19,801
Leverage	0.010	0.149	0.184	0.287	0.195	19,801
Cash	0.041	0.134	0.211	0.319	0.215	19,801
Profitability	0.141	0.268	0.257	0.391	0.461	19,801
PPE	0.099	0.190	0.234	0.324	0.176	19,801
Capex	0.022	0.040	0.053	0.068	0.048	19,801
MarketCap (in M)	413.300	1,120.985	8,742.104	3,950.937	39,791.101	19,801
KZIndex	-6.104	-1.746	-6.101	0.329	16.231	19,801
CGIndex	0.015	0.345	0.378	0.930	0.648	19,801
HHI	0.140	0.223	0.296	0.393	0.212	19,801
HHI^2	0.020	0.050	0.133	0.155	0.199	19,801
Instruments						
Russell1000to2000	0	0	0.027	0	0.026	19,801
Russell2000to1000	0	0	0.031	0	0.029	19,801
RankChange	-128	0	0.339	133	324.992	19,801

+ These are the absolute ownership shares of motivated investors and blockholders, respectively, i.e., not relative to the share of all institutional investors.

to total assets is 23.4%, and the rate of capital expenditures to total assets is 5.3%. The average market capitalization of firms in our sample is about $8.7 billion. The *KZIndex* is a measure of financial constraints, and a larger value means that firms are more financially constrained. Firms in our sample score -6.1 in the *KZIndex* on average. The average score in the corporate governance index (*CGIndex*) is 0.38. The average industry concentration is about 30%.

Finally, concerning the instruments, 2.7% of firms in our sample switch from the Russell 1000 to the Russell 2000 during our sample period, and 3.1% of firms switch from the Russell 2000 to the Russell 1000. These percentages are consistent with previous papers that have used these instruments. The change in rank for the average firm in our sample is 0.34, which means that firms on average move 34 positions down along the indexes.

1.4 Empirical Strategy

We study how different types of institutional owners influence firms' innovation strategies and outcomes. We start by estimating an Ordinary Least Squares (OLS) model as follows:

$$\begin{aligned} Innovation_{(i,t+k)} &= \alpha + \beta_1 MotivatedOwn_{(i,t)} + \beta_2 BlockOwn_{(i,t)} \\ &\quad + \gamma X_{(i,t)} + \lambda_s + \delta_t + \varepsilon_{(i,t)}, \end{aligned} \tag{1.1}$$

where i, t and s are firm, year, and industry sub-indexes, respectively. Depending on the regression, k can be 0, 1, 2, or 3, indicating that the innovation inputs or outcomes correspond to the current period, one, two, or three periods forward. The dependent variable $Innovation_{(i,t+k)}$ corresponds to different measures of innovation inputs, which are R&D spending, acquisitions, and CVC investments; and innovation outcomes, which are the yearly number of granted patents and the yearly number of citations. There are two main independent variables: $MotivatedOwn_{(i,t)}$ that measures the relative ownership held by motivated monitors, and $BlockOwn_{(i,t)}$ that measures the relative ownership held by blockholders. Control variables that capture firm and industry characteristics are included in $X_{(i,t)}$. λ_s and δ_t are industry and year fixed effects, respectively.[17] Standard errors are robust to heteroskedasticity and clustered at the firm level in all regressions.

The fixed effects included in the above OLS model are meant to capture some of the unobserved heterogeneity in the relationship between innovation and institutional ownership. For example, some industries might be more innovative and at the same time attract more institutional ownership. However, any unobserved time-varying effect at the firm level still has the potential to bias our estimates. For instance, institutional shareholders might raise their holdings and become motivated after increases in firms' potential to innovate. If that

[17] We cannot include firm fixed effects because our identification strategy exploits firms' switches between the Russell 1000 and Russell 2000 indices, and most firms switch only once during our sample period.

is the case, our claim that firms' increased innovation results from motivated institutional investors' influence would be incorrect.

We use an instrumental variables (IV) approach to address this endogeneity problem. Following several recent papers,[18] our identification strategy exploits the composition of the Russell 1000 and 2000 indexes and their annual reconstitutions to instrument our different types of institutional ownership. Every year in June, Russell Investments determines which firms are the largest one thousand firms in terms of their market capitalization as of the last trading day in May of that year. These firms are selected to constitute the Russell 1000 index for the next twelve months. The following two thousand largest firms by market capitalization constitute the Russell 2000 index. As a result, in June every year, the Russell indexes are reconstituted, and firms that belong to one index may switch to the other index; that is, they may enter or leave an index. The reason why index membership and reconstitutions affect firms' institutional ownership composition is that these indexes are value-weighted. A stock that moves from the bottom of the Russell 1000 index to the top of the Russell 2000 index will have a much larger weight in the index than before. Or vice-versa, a stock that moves from the top of the Russell 2000 to the bottom of the Russell 1000 index will have a lower weight. A firm that changes its position within the index will also experience a change in its weight. Since index-tracking institutions are compensated to minimize tracking error, financial institutions that track those indexes will have to adjust the weights of affected firms in their portfolios accordingly. Hence, affected firms' institutional ownership composition will change. In fact, all firms, affected or not, could change in terms of their weight and relative importance to the institutions that hold them (Fich et al., 2015); and any institution, index tracker or not, might be affected by index reconstitutions because of changes in firms' shareholdings due to tracker institutions.[19] Hence, our instruments are likely to satisfy the relevance condition because index reconstitutions are likely to be correlated with changes in the relative ownership of motivated, blockholder, and institutional investors.

We construct three instrumental variables to capture these effects: *Russell1000to2000*, *Russell2000to1000*, and *RankChange*. The first two instruments are indicator variables that capture switches from the Russell 1000 to 2000 index and from the Russell 2000 to 1000 index, respectively. The third variable is a continuous variable that controls for the magnitude of a firm's change in raw market capitalization along the Russell indexes from end-of-May *t-1* to end-of-May *t*. [20]

[18] Chang et al. (2015); Crane et al. (2016); Fich et al. (2015); Appel et al. (2016); Schmidt and Fahlenbrach (2017).

[19] The paper by Corum et al. (2021) shows that increases in ownership by one type of investors, for example, passive, may crowd out other types of investors, for example, active or retail investors, leading to a recomposition of firms' ownership.

[20] The firms' weight in the index is determined using their float-adjusted market capitalization, which is a proprietary measure that Russell calculates, and it is different from the raw market capitalization measure used to determine index membership (the float-adjusted market capitalization only includes those shares that are available to the public whereas raw market capitalization includes all shares issued). As Schmidt

An important issue with the instruments is that, since index assignments and reconstitutions are based on firms' (raw) market capitalization rather than being random, there could be a concern about the exogeneity of our instruments. Specifically, it could be that when a firm's market capitalization changes, its institutional ownership changes for reasons that are unrelated to index assignment or switching. As argued by Fich et al. (2015) and by Appel et al. (2016), variation in ownership becomes exogenous after controlling for firms' market capitalization. Hence, we control for firms' raw market capitalization computed with data from Compustat in all our regressions.[21]

We estimate the following IV model using two-stage least squares (2SLS):

$$\begin{aligned} Innovation_{(i,t+k)} &= \alpha + \beta_1 Motiva\hat{ted}Own_{(i,t)} + \beta_2 Block\hat{O}wn_{(i,t)} \\ &\quad + \gamma X_{(i,t)} + \lambda_s + \delta_t + \varepsilon_{(i,t)}, \end{aligned} \tag{1.2}$$

where our two types of institutional owners, *MotivatedOwn* and *BlockOwn*, are instrumented according to the following two first-stage regressions:

$$\begin{aligned} MotivatedOwn_{(i,t)} &= \alpha + \eta_1 Russell1000to2000_{(i,t)} + \eta_2 Russell2000to1000_{(i,t)} \\ &\quad + \eta_3 RankChange_{(i,t)} + \gamma X_{(i,t)} + \lambda_s + \delta_t + \mu_{(i,t)}, \end{aligned} \tag{1.3}$$

and

$$\begin{aligned} BlockOwn_{(i,t)} &= \alpha + \eta_1 Russell1000to2000_{(i,t)} + \eta_2 Russell2000to1000_{(i,t)} \\ &\quad + \eta_3 RankChange_{(i,t)} + \gamma X_{(i,t)} + \lambda_s + \delta_t + \mu_{(i,t)}. \end{aligned} \tag{1.4}$$

In some specifications, we first assess the average effect of institutional ownership before understanding the heterogeneous impact due to the different types of institutional ownership. When that is the case, we will instrument total institutional ownership using the same instruments used in the first-stage regression above.

Our IV model also includes the firm and industry characteristics included in the OLS model as well as industry and year fixed effects.

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and Fahlenbrach (2017), we argue that the ranking based on the free-float adjusted market capitalization is inappropriate for identification because it leads firms around the threshold of the Russell 1000/2000 indexes to have very different characteristics (see Schmidt and Fahlenbrach (2017) -Appendix A- for more details). It is precisely closer to the threshold where index switches occur, which is the variation exploited by our first two instruments. Systematic differences among firms above and below the threshold would invalidate random assignment. A ranking based on raw market capitalization does not suffer from the same criticism because firms classified around the threshold based on the raw market capitalization should have similar characteristics. However, it is important to stress that, since ownership changes are due to changes in firms' weights, and Russell calculates these weights based on their proprietary float-adjusted market capitalization measure, our underlying assumption, as in Schmidt and Fahlenbrach (2017), is that the actual rank and assigned weight based on the float-adjusted measure is not too different from the rank based on raw market capitalization.

[21]Since the empirical papers in the corporate finance literature usually control for firms Tobin's Q, we have estimated all our regressions using this variable instead of market capitalization as a control. We find that the results are qualitatively and quantitatively very similar to those reported in this paper.

1.5 Main Results

In this section, we study the heterogeneous effects of motivated owners and blockholders on firms' innovation inputs and output by estimating the models presented above. We first look at the impact of institutional ownership composition on firms' innovation strategy by considering three main channels that firms can use to innovate, which are: R&D expenses (Subsection 1.5.1), acquisitions of other innovative firms (Subsection 1.5.2), and CVC (Subsection 1.5.3). Then, we study the effect of the different institutional owners on patent output (Subsection 1.5.4). In all the subsections, we first present the results of the OLS model and then of the IV. For the sake of comparison, in the IV estimations, we first provide the total effect of institutional ownership, i.e., by including all types of investors in the same variable *InstOwn*. Then, we estimate our IV model presented in Section 1.4, where we distinguish between motivated monitors, blockholders, and the rest of institutional owners.

As we explained above, we expect motivated investors to monitor firms actively and get involved in firm decisions. And we expect blockholders to not engage in high-cost monitoring but to vote following standard governance practices or proxy advisors' recommendations. As a result, increases in the presence of motivated monitors should lead firms to invest in value-enhancing R&D projects, innovative acquisitions, and CVC. In contrast, increases in blockholder ownership should lead firms to reduce acquisition activity because this type of corporate decision requires high-cost information acquisition. However, blockholders may lead firms to increase R&D spending and CVC investment indirectly by improving firm governance.

1.5.1 Institutional Ownership and R&D expenditure

In this subsection, we study the effect of our different institutional owners on firms' decisions to invest in internal R&D. We present the results of our estimations in Table 1.3.

Panel A of Table 1.3 presents the OLS estimates, and Panels B and C report the IV results. Panel A presents initial evidence of the heterogeneous effects of motivated investors versus blockholders. The coefficient of motivated investors is only significant in one of the regressions; therefore, we cannot claim that this type of investor affects firms' R&D investment. On the contrary, blockholders seem to lead firms to increase spending in R&D in the current year, although not one year ahead.

As OLS results could be biased due to endogeneity, in Panels B and C, we report the results of the IV estimations. Panel B presents the first-stage regressions of the IV model, and Panel C reports the second-stage results. In Panel B, columns (2) and (3) correspond to the estimation of equations (1.3) and (1.4), whereas in column (1), the dependent variable of the first-stage regression is our measure of total institutional ownership. In all three columns, the coefficients of the three instruments are highly significant, indicating that our

Table 1.3: **Institutional investors and R&D expenses.** This table presents regression results of the effect of different institutional ownership measures on firms' R&D investments in the current year (t) and one year forward ($t+1$). We capture firms' R&D investments with two variables: *R&DChange* that captures firms' variations in R&D expenses with respect to the previous year and *R&DCut* that captures firms' reductions in R&D. Panel A presents the results of an OLS model, and Panels B and C report the estimates of IV regressions. We report the first-stage regression results in Panel B and the second-stage results in Panel C. In column (1) of Panel B and the odd columns of Panel C, we instrument institutional ownership. In Columns (2) and (3) of Panel B and the even columns of Panel C, we instrument motivated and blockholder ownership. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*). In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. We report the p-value of the difference between *MotivatedOwn* and *BlockOwn*.

Panel A: OLS R&D expenses

Dependent variable	*R&DChange*		*R&DCut*	
	(1)	(2)	(3)	(4)
	t	$t+1$	t	$t+1$
MotivatedOwn	-0.002	-0.015***	0.031	0.046
	(0.004)	(0.003)	(0.033)	(0.035)
BlockOwn	0.015***	0.002	-0.113***	0.017
	(0.004)	(0.004)	(0.029)	(0.031)
InstOwn	-0.014***	-0.004	0.139***	0.008
	(0.002)	(0.002)	(0.021)	(0.022)
R&DChange at $t-1$	-0.189***			
	(0.020)			
R&DChange at t		-0.161***		
		(0.023)		
R&DCut at $t-1$			-0.035***	
			(0.008)	
R&DCut at t				-0.024***
				(0.008)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	15904	14532	15904	14532
R^2	0.088	0.057	0.033	0.030
p-value of difference	0.001	0.000	0.000	0.507

(Table 1.3 continued)

Panel B: IV 2SLS R&D (first-stage)

Dependent variable	*InstOwn* (1) t	*MotivatedOwn* (2) t	*BlockOwn* (3) t
Russell1000to2000	0.009	-0.064***	-0.014**
	(0.011)	(0.006)	(0.007)
Russell2000to1000	0.037***	-0.016***	-0.018***
	(0.010)	(0.006)	(0.005)
RankChange	-0.009***	-0.004***	0.008***
	(0.000)	(0.000)	(0.000)
InstOwn		-0.060***	0.238***
		(0.006)	(0.006)
R&DChange at $t-1$	-0.004	0.005	0.023
	(0.033)	(0.018)	(0.025)
LnCoverage	0.092***	0.039***	-0.038***
	(0.003)	(0.002)	(0.002)
FirmSize	0.000	0.089***	-0.045***
	(0.002)	(0.002)	(0.001)
FirmAge	0.028***	0.015***	-0.007***
	(0.003)	(0.002)	(0.002)
Leverage	0.003	-0.104***	0.055***
	(0.012)	(0.011)	(0.009)
Cash	-0.050***	0.084***	-0.003
	(0.012)	(0.006)	(0.008)
Profitability	0.032***	0.011**	-0.012***
	(0.005)	(0.002)	(0.003)
PPE	-0.090***	-0.113***	0.052***
	(0.020)	(0.012)	(0.013)
Capex	-0.028	0.415***	-0.171***
	(0.057)	(0.036)	(0.038)
MarketCap	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
KZIndex	0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)
HHI	-0.081***	-0.013	0.021
	(0.028)	(0.017)	(0.018)
HHI^2	0.071**	0.036**	-0.008
	(0.029)	(0.018)	(0.018)
CGIndex	0.021***	0.001	-0.007***
	(0.003)	(0.002)	(0.002)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	15904	15904	15904

(Table 1.3 continued)

Panel C: IV 2SLS R&D (second-stage)

Dependent variable	*R&DChange*				*R&DCut*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t	t	$t+1$	$t+1$	t	t	$t+1$	$t+1$
MotivatedOwn		-0.038		0.013		0.710*		-0.141
(Instrumented)		(0.037)		(0.032)		(0.369)		(0.331)
BlockOwn		0.245***		0.098***		-1.482***		0.043
(Instrumented)		(0.030)		(0.027)		(0.243)		(0.223)
InstOwn	-0.235***	-0.066***	-0.081***	-0.022***	1.681***	0.471***	-0.086	-0.007
(Instrumented)+	(0.023)	(0.006)	(0.020)	(0.006)	(0.157)	(0.046)	(0.136)	(0.041)
R&DChange at $t-1$	-0.195***	-0.200***						
	(0.023)	(0.022)						
R&DChange at t			-0.171***	-0.170***				
			(0.027)	(0.027)				
R&DCut at $t-1$					-0.051***	-0.038***		
					(0.009)	(0.009)		
R&DCut at t							-0.022**	-0.023***
							(0.009)	(0.008)
LnCoverage	0.024***	0.013***	0.004**	0.000	-0.175***	-0.109***	0.043***	0.041***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.017)	(0.012)	(0.014)	(0.011)
FirmSize	-0.002***	0.012***	0.003***	0.006**	0.027***	-0.103***	-0.018***	-0.003
	(0.001)	(0.003)	(0.001)	(0.003)	(0.006)	(0.026)	(0.005)	(0.025)
FirmAge	0.008***	0.003***	0.000	-0.001**	-0.037***	-0.014	0.034***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.008)	(0.008)
Leverage	-0.002	-0.020***	-0.014**	-0.018***	0.011	0.175***	-0.045*	-0.063
	(0.006)	(0.007)	(0.006)	(0.006)	(0.031)	(0.042)	(0.025)	(0.039)
Cash	-0.017***	-0.002	0.005	0.008*	0.184***	0.039	-0.096***	-0.079**
	(0.005)	(0.005)	(0.004)	(0.005)	(0.033)	(0.042)	(0.029)	(0.039)
Profitability	0.000	-0.004*	0.001	-0.001	-0.036***	-0.011	0.007	0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.013)	(0.011)	(0.011)	(0.010)
PPE	-0.025***	-0.021***	-0.011**	-0.008	0.187***	0.204***	0.127**	0.115*
	(0.007)	(0.006)	(0.005)	(0.006)	(0.058)	(0.060)	(0.050)	(0.060)
Capex	0.068***	0.132***	0.004	0.018	-0.262*	-0.860***	0.171	0.244
	(0.019)	(0.023)	(0.016)	(0.020)	(0.150)	(0.184)	(0.134)	(0.183)
MarketCap	-0.000***	-0.000	-0.000***	-0.000*	0.000***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KZIndex	0.000***	0.000***	-0.000***	-0.000***	-0.002***	-0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HHI	-0.024***	-0.011	-0.002	0.004	0.283***	0.194***	-0.021	-0.015
	(0.009)	(0.008)	(0.007)	(0.007)	(0.083)	(0.075)	(0.073)	(0.072)
HHI^2	0.022**	0.009	0.003	-0.004	-0.261***	-0.185**	0.011	0.008
	(0.009)	(0.007)	(0.006)	(0.006)	(0.085)	(0.078)	(0.075)	(0.075)
CGIndex	0.005***	0.002**	0.001	-0.000	-0.037***	-0.014*	0.006	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.008)	(0.008)	(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15904	15904	14532	14532	15904	15904	14532	14532
R^2	-0.739	-0.337	-0.048	-0.015	-0.363	-0.154	0.026	0.025
C-D F-statistic	123.02	47.36	116.39	46.85	121.42	47.51	116.15	46.98
p-value of difference		0.000		0.004		0.000		0.427

+ The variable *InstOwn* is instrumented in columns (1), (3), (5), and (7).

instruments have power.[22] As we explained in Section 1.4, Russell index tracker institutions will adjust their portfolio firms' holdings to reflect changes in firms' weights after index recompositions. Still, non-index tracker institutions might also be indirectly affected by recompositions due to the trading of index tracker funds. These adjustments are likely to induce non-trivial changes in firms' ownership composition. As a result, the net effect on our different types of institutional ownership is difficult to predict. From our results, we observe that motivated ownership decreases relative to total institutional ownership when firms switch from the Russell 1000 to the Russell 2000 index. Specifically, ownership by motivated monitors is reduced by 6 percentage points (i.e., about 40% with respect to the unconditional mean). This result is consistent with Fich et al. (2015), who also observe a decrease. We also observe that both motivated ownership and blockholder ownership decrease when firms switch from the Russell 2000 to the Russell 1000 index, which is what we would expect index tracker institutions to do because, after switching, firm weights decrease. These rebalancing adjustments seem to be partly absorbed by the rest of the institutional owners for whom ownership increases. Also, when firms move to lower ranks along indexes, motivated ownership decreases relative to total institutional ownership, and blockholder ownership increases suggesting that institutional owners adjust their holdings in response to changes in market capitalization.

In Panel C of Table 1.3, the odd columns capture the causal effect of total institutional ownership on R&D investment because the variable institutional ownership is instrumented. In the even columns, both motivated ownership and blockholder ownership are instrumented, and institutional ownership is just a control in these regressions. Regarding the effect of institutional investors in general (i.e., odd regressions), the coefficients of institutional ownership are significant at the 1% level in three of the four regressions. These coefficients suggest that an increase in firms' institutional ownership, prompted by changes in the composition of the Russell 1000 or Russell 2000 indexes, leads firms to reduce and even cut R&D expenses during the same year and to continue reducing R&D spending one year later. When we distinguish between motivated owners and blockholders, we observe that these two types of investors influence firms in strikingly different ways and also different from the rest of institutional owners. Specifically, when the percentage of institutional ownership in the hands of blockholders increases, firms tend to increase their investment in R&D both in the current period and one year later. In contrast, an increase in the ownership by motivated investors does not generally affect firms' R&D investment. The significant p-value of the difference between the impact of blockholders versus the motivated investors (reported at the bottom of the table) in all regressions corroborates these heterogeneous effects. The coefficient of institutional ownership in the even regressions is negative and significant, suggesting that the rest of institutional owners, which are not motivated nor blocks, are negatively related to firms' spending in R&D.

These results confirm our predictions for the effect of blockholder investors, which, as we argued in the introduction, might be encouraging firm R&D spending indirectly through improvements in corporate governance. The results do not verify our prediction that motivated monitors will increase R&D investment. Still, we can observe a heterogeneous effect of these two types of investors on firm R&D.

[22] The Cragg-Donald F-statistics of the regressions are all higher than the Stock-Yogo weak identification test critical values, which rejects the hypothesis of weak instruments. The overidentification test (the Hansen J statistics) has high p-values (untabulated). It indicates that we cannot reject the null hypothesis that the IVs are valid instruments.

Table 1.4: **Institutional investors and acquisitions.** This table presents regression results of the effect of different institutional ownership measures on firms' acquisition activity in the current year (t) and one and two years forward (*t+1* and *t+2*). We capture firms' acquisition activity with two variables: the dummy *Acquisition* that takes the value one if a firm acquires one or more companies in the year and equals zero otherwise and *LnAcquisitions* that is the natural logarithm of (one plus) the total number of acquired companies. Panel A presents the results of an OLS model, and Panels B and C report the second-stage estimates of IV regressions. In the odd columns of Panels B and C, we instrument institutional ownership, and in the even columns of Panels B and C, we instrument motivated and blockholder ownership. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*). In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. We report the p-value of the difference between *MotivatedOwn* and *BlockOwn*.

Panel A: OLS Acquisitions

Dependent variable		*Acquisition*			*LnAcquisitions*	
	(1)	(2)	(3)	(4)	(5)	(6)
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
MotivatedOwn	0.132***	0.203***	0.180***	0.164***	0.212***	0.173***
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)
BlockOwn	-0.102***	-0.072***	-0.060***	-0.084***	-0.065***	-0.053***
	(0.021)	(0.022)	(0.022)	(0.019)	(0.019)	(0.019)
InstOwn	0.087***	0.075***	0.066***	0.064***	0.061***	0.051***
	(0.017)	(0.018)	(0.019)	(0.016)	(0.016)	(0.017)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19801	18844	17818	19801	18844	17818
R^2	0.095	0.078	0.068	0.112	0.093	0.083
p-value of difference	0.000	0.000	0.000	0.000	0.000	0.000

The rest of the control variables in the regressions have the expected sign. Larger firms and firms with more cash are more likely to increase (and less likely to cut) R&D one year ahead, and firms with more fixed assets or more leverage are less likely to increase (or more likely to cut) R&D. Also, firms with lower financial constraints and better corporate governance are more likely to increase R&D.

(Table 1.4 continued)

Panel B: IV 2SLS Acquisition dummy (second-stage)

Dependent variable	*Acquisition*					
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t	$t+1$	$t+1$	$t+2$	$t+2$
MotivatedOwn		0.456*		0.498**		0.125
(Instrumented)		(0.235)		(0.230)		(0.228)
BlockOwn		-0.561***		-0.538***		-0.459***
(Instrumented)		(0.154)		(0.153)		(0.154)
InstOwn	0.818***	0.194***	0.804***	0.179***	0.537***	0.139***
(Instrumented)+	(0.098)	(0.030)	(0.103)	(0.029)	(0.096)	(0.027)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19801	19801	18844	18844	17818	17818
R^2	-0.084	0.022	-0.094	0.009	-0.019	0.024
C-D F-statistics	142.80	59.08	142.56	58.20	145.47	57.86
p-value of difference		0.000		0.000		0.000

+ The variable *InstOwn* is instrumented in columns (1), (3), and (5).

Panel C: IV 2SLS Number of acquisitions (second-stage)

Dependent variable	*LnAcquisition*					
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t	$t+1$	$t+1$	$t+2$	$t+2$
MotivatedOwn		0.551***		0.452**		0.143
(Instrumented)		(0.189)		(0.193)		(0.193)
BlockOwn		-0.522***		-0.540***		-0.383***
(Instrumented)		(0.130)		(0.132)		(0.128)
InstOwn	0.807***	0.168***	0.773***	0.165***	0.460***	0.112***
(Instrumented)+	(0.088)	(0.026)	(0.090)	(0.025)	(0.079)	(0.023)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19801	19801	18844	18844	17818	17818
R^2	-0.119	0.023	-0.118	0.015	-0.007	0.039
C-D F-statistics	142.80	59.08	142.56	58.20	145.47	57.86
p-value of difference		0.000		0.000		0.000

+ The variable *InstOwn* is instrumented in columns (1), (3), and (5).

1.5.2 Institutional Owners and Acquisitions

In this subsection, we study whether motivated monitors and blockholder investors affect firms' acquisition activity differently. According to our previous arguments, motivated monitors have incentives to gather costly information to understand the value of the proposed acquisitions by management. They will also use this information to inform the rest of the investors and convince them to vote with them. Since managers anticipate this behavior, they will propose mostly value-enhancing acquisitions. Therefore, we predict that increases in motivated investors' ownership relative to other institutional investors' ownership lead to increases in firms' likelihood of acquiring other companies. As these acquisitions are value-enhancing, we also expect the acquired companies to be more innovative. In contrast, as we argued above, blockholders do not have incentives to acquire costly information. We expect that, in equilibrium, an increase in blockholder ownership relative to other institutional ownership will make firms less likely to acquire other firms. We run our regression model presented in Section 1.4 and report the results in Table 1.4.

Panel A of Table 1.4 shows the results of the OLS estimates, and Panels B and C the IV results. In Panel B, the dependent variable corresponds to a dummy variable equal to 1 when a firm acquires one or more firms that year and 0 otherwise. By looking at Panel B, we can see that institutional investors overall increase the likelihood that firms engage in acquisitions (odd columns). However, when we distinguish between motivated investors and blockholders (even columns), we observe that motivated investors and blockholders have opposite effects on firm acquisitions, as predicted. An increase in the presence of motivated monitors relative to other institutional investors significantly increases the probability of acquisitions, both in the current year and one year later. Specifically, a one percentage point increase in institutional ownership by motivated investors relative to other institutional owners raises the probability that a firm acquires a target company by about 0.46%. In contrast, an increase in blockholder ownership reduces firms' likelihood of acquiring other firms up to two years later. Specifically, a one percentage point increase in blockholder ownership reduces the probability that a firm acquires a target company by about 0.56%. In Panel C, the dependent variable is the natural logarithm of (one plus) the number of firms' acquisitions in a year. The results of regressions in Panel C are consistent with those in Panel B.

Since our final goal is to understand the effect of heterogeneous institutional owners on innovation, we test whether, conditional on acquiring, these investors lead firms to acquire more (or less) innovative targets. In this setting, both our OLS and IV models of Section 1.4 could suffer from potential selection bias because we only observe target firms' innovativeness for acquisitions that take place. However, firms' decisions to acquire other companies are not random. To address this selection problem, we use a two-step Heckman selection model (Heckman, 1979). In the first-stage regression, we need to include an exogenous variable that significantly affects firms' likelihood of acquiring other firms (i.e., it is relevant) but is not related to target firms' innovativeness (i.e., it is exogenous).

Table 1.5: **Institutional investors and acquisitions innovativeness.** This table presents regression results of the effect of different institutional ownership measures on the innovativeness of the acquired firms in the current year (t) and one and two years forward (*t+1* and *t+2*). We capture the innovativeness of the acquired firms with two variables: *LnTargPatent* and *LnTargCite* that are the natural logarithms of (one plus) the cumulative number of patents and citations, respectively, on average of the acquired companies. Panel A presents the results of an OLS model, and Panel B reports the second-stage results of the two-step Heckman selection model (Heckman, 1979). We use the exogenous variable *FlowtoStock* (see Wardlaw, 2020) that captures the fire sale pressure of mutual funds. In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. We report the p-value of the difference between *MotivatedOwn* and *BlockOwn*.

Panel A: OLS target innovativeness

Dependent variable		*LnTargPatent*			*LnTargCite*	
	(1)	(2)	(3)	(4)	(5)	(6)
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
MotivatedOwn	0.396**	0.543***	0.392**	0.571***	0.716***	0.533***
	(0.180)	(0.184)	(0.175)	(0.201)	(0.204)	(0.189)
BlockOwn	0.043	0.154	0.143	0.078	0.173	0.204
	(0.147)	(0.149)	(0.164)	(0.162)	(0.164)	(0.178)
InstOwn	0.087	0.114	0.135	0.090	0.118	0.158
	(0.099)	(0.102)	(0.102)	(0.111)	(0.113)	(0.114)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2966	2853	2662	2966	2853	2662
R^2	0.184	0.182	0.183	0.181	0.179	0.180
p-value of difference	0.073	0.058	0.222	0.026	0.017	0.141

Following Wardlaw (2020), we use the variable Flow-to-Stock as an instrument in the first-stage regression. The idea behind this strategy is that large investor redemptions might put pressure on mutual funds to sell the stocks they own. Funds' sales of stocks, if sufficiently large, put downward pressure on firms' stock prices for reasons that are unrelated to firm fundamentals. The variable Flow-to-Stock captures the relative flow pressure on each stock's price as a percentage of the stock owned by each fund. Changes in firm valuations (i.e., prices) may change firms' M&A activity without being related to firm fundamentals or the innovativeness of the target firms they acquire.[23] In the second-stage regressions of the

[23]The use of extreme mutual fund outflows as an identification strategy is first due to Edmans et al. (2012). After this contribution, several finance papers have used this strategy to study different corporate decisions, such as Bonaime et al. (2018) and Lou and Wang (2018). However, Wardlaw (2020) criticizes

(Table 1.5 continued)
Panel B: Heckman target innovativeness

Dependent variable		*LnTargPatent*			*LnTargCite*	
	(1)	(2)	(3)	(4)	(5)	(6)
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
MotivatedOwn	0.527***	0.670***	0.400**	0.693***	0.780***	0.499**
	(0.185)	(0.214)	(0.179)	(0.199)	(0.231)	(0.195)
BlockOwn	-0.312	0.055	0.136	-0.256	0.123	0.232
	(0.291)	(0.197)	(0.180)	(0.315)	(0.213)	(0.197)
InstOwn	0.332*	0.206	0.142	0.322	0.165	0.129
	(0.197)	(0.151)	(0.127)	(0.213)	(0.163)	(0.139)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Censored obs	10685	10798	10989	10685	10798	10989
Uncensored obs	2966	2853	2662	2966	2853	2662
p-value of difference	0.030	0.061	0.294	0.023	0.064	0.333

two-step Heckman selection model, we test the effects of our different types of institutional investors on target firms' innovativeness measured by the natural logarithm of (one plus) the average target firm's cumulative number of patents and citations in the current year, one year, and two years later.

Table 1.5 presents the results of these regressions. Panel A of Table 1.5 reports the OLS results, and Panel B reports the results of the second stage of the two-step Heckman selection model. The first-stage results (untabulated) show that the variable Flow-to-Stock has explanatory power. The OLS results and Heckman's two-stage regression results show very similar findings. When the presence of motivated investors increases, firms tend to acquire target companies with a significantly larger number of patents and citations. Instead, blockholder ownership and other types of institutional ownership seem to have no effect. These results suggest that motivated investors induce firms to use the acquisition channel to acquire external know-how, patents, and other innovative assets that can stimulate and increase the acquiring firms' innovation output.

1.5.3 Institutional Owners and Corporate Venture Capital Investments

Another channel that firms can use to boost their innovation is via CVC investments in start-ups. These start-ups may serve as a window to cutting-edge technologies and

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the variable MFFlow (Mutual Fund Flow) used in Edmans et al. (2012) and the follow-up papers by showing that it is correlated with firm fundamentals, which violates the exclusion restriction. Wardlaw (2020) constructs a new variable, called Flow-to-Stock, which is orthogonal to firm fundamentals (i.e., stock returns and turnover). This is the variable that we use in our setting.

Table 1.6: **Institutional investors and CVC investments.** This table presents regression results of the effect of different institutional ownership measures on the CVC investments in the current year (t) and one and two years forward (*t+1* and *t+2*). We capture the CVC investment with the dummy *CVC investment* that takes the value one if a firm's CVC fund invests in star-ups and zero otherwise. Panel A presents the results of an OLS model, and Panel B reports the second-stage estimates of IV regressions. In the odd columns of Panel B, we instrument institutional ownership, and in the even columns of Panel B, we instrument motivated and blockholder ownership. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*). In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. We report the p-value of the difference between *MotivatedOwn* and *BlockOwn*.

Panel A: OLS CVC investments

Dependent variable	*CVC investments*		
	(1)	(2)	(3)
	t	$t+1$	$t+2$
MotivatedOwn	0.090***	0.094***	0.075***
	(0.021)	(0.020)	(0.020)
BlockOwn	0.031***	0.024***	0.015**
	(0.007)	(0.007)	(0.007)
InstOwn	-0.014*	-0.005	0.010
	(0.007)	(0.007)	(0.008)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	19801	18844	17818
R^2	0.147	0.164	0.163
p-value of difference	0.000	0.000	0.000

innovative know-how that firms can incorporate in their R&D units by either developing similar ideas in-house or acquiring the start-up. In this subsection, we estimate the potential heterogeneous effects of institutional owners on firms' CVC investments. We present the regression results in Table 1.6.

In Table 1.6, OLS results are in Panel A and IV results in Panel B. Both motivated and block ownership are positively related to corporate investments in venture capital (Panel A). However, this relationship is causal only for motivated investors (panel B). An increase of one percentage point in a firm's ownership by motivated investors increases

(Table 1.6 continued)
Panel B: IV 2SLS CVC investments (second-stage)

Dependent variable	*CVC investments*					
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t	$t+1$	$t+1$	$t+2$	$t+2$
MotivatedOwn		0.182**		0.233***		0.143**
(Instrumented)		(0.090)		(0.064)		(0.063)
BlockOwn		0.053		0.029		0.009
(Instrumented)		(0.058)		(0.049)		(0.045)
InstOwn	0.029	-0.015	0.088***	-0.000	0.071**	0.013
(Instrumented)+	(0.035)	(0.011)	(0.033)	(0.009)	(0.028)	(0.008)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19801	19801	18844	18844	17818	17818
R^2	0.129	0.131	0.133	0.142	0.143	0.150
C-D F-statistics	142.80	59.08	142.56	58.20	145.47	57.86
p-value of difference		0.021		0.000		0.000

+ The variable *InstOwn* is instrumented in columns (1), (3), and (5).

firms' probability of investing in CVC by about 0.2%. The same increase in blockholder ownership does not significantly affect firms' CVC investments. These results show another source of institutional investor heterogeneity regarding their effects on firms' innovation strategy.

1.5.4 Institutional Owners and Innovation outcomes

We now turn to investigate whether the heterogeneous influence of distinct institutional owners on firms' innovation channels results in significant and differential changes in firms' innovation output. As we explained above, previous research suggests that investing in external innovation can increase the efficiency and effectiveness of firms' internal innovation processes leading to more productive inventions. Our results in the previous sections suggest that firms with more motivated monitors rely more on external innovation from acquisitions or CVC investments to increase their innovation production. In contrast, firms with more blockholders tend to produce innovation that comes mostly from developing their internal R&D. Given these results, we expect firms with more motivated investors to produce a larger amount of innovation output than firms with more blockholder ownership. To see this, we study the effect on firms' future patents and citations.

Table 1.7 presents the results of our estimations. In the IV regressions (Panel B), both motivated monitors and blockholders have a positive and significant effect on firms' future number of patents (columns (1) to (4) of panel B). Specifically, for the average

Table 1.7: **Institutional investors and innovation outputs.** This table presents regression results of the effect of different institutional ownership measures on the innovation outcomes of the firm two and three years forward (*t+2* and *t+3*). We capture the firm's innovation output with two variables: *LngPatents* and *LnCitations* that are the natural logarithms of (one plus) the number of patents and citations of the firm each year. Panel A presents the results of an OLS model, and Panel B reports the second-stage estimates of IV regressions. In the odd columns of Panel B, we instrument institutional ownership, and in the even columns of Panel B, we instrument motivated and blockholder ownership. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*). In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively. We report the p-value of the difference between *MotivatedOwn* and *BlockOwn*.

Panel A: OLS Innovation outputs

Dependent variable	*LnPatents*		*LnCitations*	
	(1)	(2)	(3)	(4)
	$t+2$	$t+3$	$t+2$	$t+3$
MotivatedOwn	0.725***	0.679***	0.796***	0.751***
	(0.165)	(0.156)	(0.173)	(0.163)
BlockOwn	0.072	0.088	0.045	0.071
	(0.080)	(0.077)	(0.087)	(0.083)
InstOwn	0.008	0.074	0.056	0.106
	(0.088)	(0.082)	(0.093)	(0.087)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	12601	12601	12601	12601
R^2	0.476	0.461	0.446	0.432
p-value of difference	0.000	0.000	0.000	0.000

company with 30 patents, when motivated ownership increases by one percentage point, the number of patents increases by about 0.69 (an increase of 2.3%); and when blockholder ownership increases by one percentage point, the number of patents increases by about 0.26 (an increase of about 0.9%). These coefficients are economically and significantly different from each other, as we can observe from the p-values of the differences reported at the bottom of the table.

Similarly, when we take citations as a measure of firms' innovation output (columns (5) to (8) of Panel B), we observe that motivated owners have a significantly larger effect than

(Table 1.7 continued)
Panel B: IV 2SLS Innovation outputs

Dependent variable		*LnPatents*				*LnCitations*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$t+2$	$t+2$	$t+3$	$t+3$	$t+2$	$t+2$	$t+3$	$t+3$
MotivatedOwn		2.224***		2.132***		2.060***		2.027***
(Instrumented)		(0.550)		(0.547)		(0.599)		(0.597)
BlockOwn		0.852**		0.719**		0.616		0.621
(Instrumented)		(0.358)		(0.350)		(0.392)		(0.387)
InstOwn	0.260	-0.090	0.393**	0.001	0.428*	-0.012	0.467**	0.043
(Instrumented)+	(0.196)	(0.068)	(0.190)	(0.066)	(0.221)	(0.074)	(0.214)	(0.073)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12601	12601	12601	12601	12601	12601	12601	12601
R^2	0.387	0.369	0.383	0.367	0.354	0.348	0.356	0.345
C-D F-statistics	135.44	50.14	135.44	50.14	135.44	50.14	135.44	50.14
p-value of difference		0.000		0.000		0.000		0.000

+ The variable *InstOwn* is instrumented in columns (1), (3), (5), and (7).

blockholders (and the difference is significant at the 1% level). For the average company with 343 citations, a one percentage point increase in the ownership by motivated monitors relative to other institutional investors increases firms' citations by about 7 (an increase of 2.03%). In contrast, an increase of one percentage point in blockholder ownership increases firms' citations by about 2 (an increase of 0.6%, although this effect is significant only at the 11% level).

Overall, we observe that while both motivated and blockholder investors increase firms' future patents significantly, the effect of motivated ownership increases on firms' future number of patents is about 2.5 times larger than that of blockholders. The differential effect on firm citations is also significant and large: firms that experience an increase in motivated investors' ownership produce about 3.5 times more citations than firms that experience increases in blockholder ownership. These results are in line with previous studies that show that firms with an open approach to innovation, i.e., not only producing internally but also acquiring external innovation, can generate a larger number of patent and citation output. Interestingly, in our context, this open innovation approach seems to be nurtured by the presence of motivated institutional owners.

1.6 Lazy Manager vs Career Concerns

The results in the previous sections confirm our hypotheses that motivated monitors and blockholders have heterogeneous effects on firms' innovation strategies and that, as a result, firms obtain a different innovation output. In this section, we want to shed light on the mechanisms behind these heterogeneous outcomes. On the one hand, we argue that motivated investors encourage firms to acquire innovation because these investors have incentives to monitor managers, evaluate managerial proposals, and affect managers' fate by sharing the information they collect with other shareholders. In a career concern model à la Holmström (1999), even if managers dislike the risk that innovation involves, in particular, because they risk being fired, monitoring by motivated investors may mitigate that risk by insulating managers from the potentially bad outcomes that can result from pure stochastic reasons. On the other hand, blockholders also encourage firm innovation, but it is probably for a different reason. As we argue above, blockholders that are not motivated monitors do not have incentives to monitor or get involved in complex decisions. Instead, they vote in shareholder meetings on issues that require a low cost of acquiring information, or they vote based on uniform rules or following the ISS recommendations. According to the lazy manager hypothesis (Hart, 1983; Bertrand and Mullainathan, 2003), blockholders may encourage managers to innovate by improving corporate governance.[24]

We test the presence of these mechanisms using the results of the model of Aghion et al. (2013), which yields opposite predictions of these two mechanisms on the interaction between institutional ownership and competition. According to Aghion et al. (2013), the career concerns model predicts that institutional investors' positive effect on innovation will be stronger when competition is more intense because the probability of unsuccessful risky innovations and the associated bad outcomes is larger. In contrast, the lazy manager model predicts that, with fierce competition, institutional investor presence is less necessary because competition is an external governance mechanism that disciplines managers to work hard since it increases the threat of takeover or bankruptcy. Hence, the career concerns hypothesis predicts complementarity between institutional ownership and intense competition, while the lazy manager hypothesis predicts substitution. In other words, a positive effect of the interaction between investor ownership and competition on innovation provides support for the first model, and a negative interaction offers support for the second model.

To test these mechanisms, we include in our regression model an interaction term between motivated ownership and blockholder ownership with an indicator variable that is equal to one if the company operates in a highly competitive industry (i.e., industry-year is below the median of the Herfindahl-Hirschman index) and zero otherwise.

We report the results of our IV estimations in Table 1.8 (we exclude OLS results for brevity). As we can see, the interaction term between motivated ownership and intense competition (odd columns) is positive and significant for both patents and citations, confirming the monitoring role of motivated investors. In contrast, the interaction term between blockholder ownership and intense competition is negative and significant (even

[24]For example, a recent paper by Balsmeier et al. (2017) shows that improvements in corporate governance in the form of more independent boards have significant positive effects on innovation.

Table 1.8: **Institutional investors, industry competition, and innovation outputs.** This table presents the second-stage IV regression results of the effect of the interaction between institutional ownership measures and high industry competition (a dummy equal to one if the HHI is below the median and zero otherwise) on the innovation outcomes of the firm two and three years forward (*t+2* and *t+3*). We capture the firm's innovation output with two variables: *LnPatents* and *LnCitations* that are the natural logarithms of (one plus) the number of patents and citations of the firm each year. In the odd columns, we instrument motivated ownership and its interaction; in the even columns, we instrument block ownership and its interaction. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*), as well as the interaction of these variables with the high industry competition dummy. In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively.

IV 2SLS Innovation outputs & high-competitive industries

Dependent variable		*LnPatents*				*LnCitations*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$t+2$	$t+2$	$t+3$	$t+3$	$t+2$	$t+2$	$t+3$	$t+3$
MotivatedOwn	1.368***	0.745***	1.241**	0.667***	1.279**	0.781***	1.261**	0.735***
(Instrumented)$^+$	(0.487)	(0.107)	(0.486)	(0.107)	(0.539)	(0.116)	(0.530)	(0.116)
BlockOwn	0.260***	0.651**	0.295***	0.552*	0.231**	0.641*	0.257***	0.505
(Instrumented)$^+$	(0.085)	(0.330)	(0.084)	(0.314)	(0.095)	(0.369)	(0.093)	(0.352)
InteractMotivatedOwn	0.792*		1.104**		1.025**		0.976**	
(Instrumented)$^+$	(0.455)		(0.445)		(0.508)		(0.496)	
InteractBlockOwn		-0.913**		-0.972**		-1.193**		-0.927*
(Instrumented)$^+$		(0.461)		(0.444)		(0.522)		(0.504)
InstOwn	-0.019	-0.018	0.039	0.073	0.021	0.049	0.074	0.106*
	(0.046)	(0.059)	(0.046)	(0.057)	(0.050)	(0.065)	(0.049)	(0.063)
highComp	-0.089	0.156**	-0.143*	0.159**	-0.134	0.187**	-0.127	0.150**
	(0.075)	(0.068)	(0.073)	(0.066)	(0.084)	(0.077)	(0.081)	(0.074)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12601	12601	12601	12601	12601	12601	12601	12601
R^2	0.375	0.389	0.362	0.384	0.343	0.355	0.340	0.356
C-D F-statistics	43.92	63.30	43.92	63.30	43.92	63.30	43.92	63.30

$^+$ The variables *MotivatedOwn* and *InteractMotivatedOwn* are instrumented in columns (1), (3), (5), and (7). The variables *BlockOwn* and *InteractBlockOwn* are instrumented in columns (2), (4), (6), and (8).

columns), confirming the governance role of blockholders. The fact that the effect of blockholder ownership on innovation is positive and significant in industries with less intense competition and it switches to negative and significant for more competitive industries provides further evidence that blockholders have a governance role. Their governance effect becomes less needed once competition is fiercer because intense competition disciplines managers to work hard.

1.7 Institutional Owners and Financial Analysts

In this section, we further explore the monitoring and governance mechanisms behind the heterogeneous effects of motivated and blockholder investors on innovation. As we argued above, motivated investors monitor managers by collecting costly information and sharing this information with other shareholders to affect corporate strategy. In that sense, motivated investors' monitoring role crucially relies on obtaining access to information. As shown in Guo et al. (2019), financial analysts reduce information asymmetries between investors and the market by releasing their reports and recommendations to investors. By reducing information asymmetries, financial analysts have a positive and significant impact on corporate innovation. We hypothesize that the effects of motivated investors and financial analysts on innovation reinforce each other. Financial analysts produce information about firms facilitating the monitoring task of motivated investors. In contrast, as we saw above, blockholders influence innovation through improvements in corporate governance. Since, similarly to competition, financial analysts are viewed as an external corporate governance mechanism (Chen et al., 2015), we expect that blockholders and financial analysts are substitutes in increasing firm innovation.

To investigate the previous hypotheses, we construct the indicator variable *highCov*, which is equal to one for those firm-years in which the number of analysts covering a firm is above the average number of analysts in our sample (i.e., above 9.47) and zero otherwise. That is, *highCov* identifies those firm-years where coverage by financial analysts is extensive. We include this indicator variable and its interaction with our different institutional ownership variables in a regression where the dependent variable corresponds to firms' future patents or citations. We present the IV results in Table 1.9 (for brevity, we exclude OLS results).

The IV results provide support for our hypotheses. The odd columns show that motivated investors' ownership does not affect firms' future patents and citations when analyst coverage is low. In contrast, the interaction term between motivated ownership and high analyst coverage is positive and significant, indicating that the effect of motivated ownership on firm innovation is driven by those firms with high analyst coverage. These results suggest that motivated owners and financial analysts are complements in fostering firm innovation and that this is due to an information effect: companies with more financial analysts have more information available, in the form of analyst reports, analyst recom-

Table 1.9: **Institutional investors, financial analysts, and innovation outputs.** This table presents the second-stage IV regression results of the effect of the interaction between institutional ownership measures and high coverage by financial analysts (a dummy equal to one if the coverage is above the median and zero otherwise) on the innovation outcomes of the firm two and three years forward (*t+2* and *t+3*). We capture the firm's innovation output with two variables: *LnPatents* and *LnCitations* that are the natural logarithms of (one plus) the number of patents and citations of the firm each year. In the odd columns, we instrument motivated ownership and its interaction; in the even columns, we instrument block ownership and its interaction. We use three instrumental variables (see Schmidt and Fahlenbrach, 2017) that capture switches from the Russell 1000 to the Russell 2000 index (*Russell1000to2000*), switches from the Russell 2000 to the Russell 1000 index (*Russell2000to1000*), and changes in the firms' rank within one index (*RankChange*), as well as the interaction of these variables with the high coverage dummy. In all regressions, we include a battery of controls and fixed effects that are usual in the literature. All variables are defined in Table 1.1. Robust standard errors clustered at the firm level are in parentheses. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% level, respectively.

IV 2SLS Innovation outputs & financial analysts

Dependent variable		*LnPatents*				*LnCitations*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$t+2$	$t+2$	$t+3$	$t+3$	$t+2$	$t+2$	$t+3$	$t+3$
MotivatedOwn	-0.929	-0.156	-0.597	-0.261	-0.643	-0.119	-0.673	-0.230
(Instrumented)$^+$	(0.848)	(0.309)	(0.833)	(0.314)	(0.961)	(0.335)	(0.932)	(0.342)
BlockOwn	0.026	1.708***	0.082	1.597***	0.009	1.606***	0.036	1.678***
(Instrumented)$^+$	(0.098)	(0.530)	(0.097)	(0.526)	(0.110)	(0.579)	(0.108)	(0.577)
InteractMotiCov	2.582***		2.353***		2.285**		2.355**	
(Instrumented)$^+$	(0.847)		(0.830)		(0.955)		(0.924)	
InteractBlockCov		-6.213***		-6.396***		-6.304***		-6.738***
(Instrumented)$^+$		(1.916)		(1.941)		(2.083)		(2.121)
InstOwn	0.089	0.082	0.154***	0.189**	0.129**	0.150*	0.196***	0.231***
	(0.054)	(0.074)	(0.054)	(0.075)	(0.060)	(0.080)	(0.058)	(0.082)
highCov	-0.194***	1.016***	-0.170**	1.050***	-0.153*	1.044***	-0.159**	1.113***
	(0.072)	(0.304)	(0.071)	(0.308)	(0.081)	(0.331)	(0.078)	(0.337)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12601	12601	12601	12601	12601	12601	12601	12601
R^2	0.386	0.262	0.381	0.247	0.358	0.241	0.353	0.216
C-D F-statistics	47.71	8.37	47.71	8.37	47.71	8.37	47.71	8.37

$^+$ The variables *MotivatedOwn* and *InteractMotiCov* are instrumented in columns (1), (3), (5), and (7). The variables *BlockdOwn* and *InteractBlockCov* are instrumented in columns (2), (4), (6), and (8).

mendations, press releases, etc., which makes it easier for motivated investors to collect information and monitor firms. The results for blockholders are in the even columns. The effect of blockholders on firm innovation is positive for firms with low analyst coverage and negative for firms with high analyst coverage. Thus, blockholders and financial analysts are substitutes in encouraging firms to innovate.

1.8 Conclusion

This paper inquires about the heterogeneous effects of different institutional owners on firm innovation. We classify institutional ownership as motivated ownership if the ownership stake represents a large holding from the point of view of the institutional owner's portfolio and as blockholder ownership if the ownership stake represents a large holding from the firm's point of view.

Our results provide extensive support for the heterogeneous effects of institutional investors. We find that motivated investors encourage firms to acquire external innovation and invest in CVC. In contrast, blockholders shy away from innovative acquisitions and CVC investments and rely more on developing their internal R&D. Both types of investors have a positive and significant effect on firm innovation by increasing firms' future patents and citations. However, firms that experience increases in motivated ownership relative to total institutional ownership generate 2.5 times more patents and 3.5 times more citations than firms with increases in blockholder ownership.

We also shed light on the mechanisms behind these effects. Motivated investors have incentives to obtain information from firms, and as a result, they get involved in complex decisions such as innovative acquisitions. Indeed, we find that access to information is crucial for motivated investors since we observe that their effect is reinforced when companies have more financial analysts who also require, collect, and disseminate information from firms. Then, motivated investors encourage firm innovation because their superior information allows them to insulate managers from the potential bad outcomes of risky investments in innovation that may be due to pure bad luck. Following the predictions of Aghion et al. (2013), we find evidence of the career concerns hypothesis because we observe that the effect of motivated ownership on innovation is more substantial when competition is more intense.

In contrast, blockholders, who do not have incentives to monitor managers actively, cast their votes in shareholder meetings to influence innovation decisions through corporate governance improvements. We find evidence of this corporate governance effect by showing that the impact of blockholders on innovation is stronger when other external corporate governance mechanisms, such as intense competition or high analyst coverage, are not present.

Overall, our paper contributes to the scarce literature on institutional owners' heterogeneous effects on corporate decisions and performance. By focusing on firm innovation, we show that firms' shareholder composition affects firm decisions about the innovation process and that this has significant consequences for the final innovation outcome. Our paper also contributes to the literature concerned about institutional investors' increasing reliance on uniform recommendations by proxy advisor firms.

Chapter 2

Common Ownership and the Market for Technology

2.1 Introduction

Innovation, technological progress, and new products drive economic growth and development (Schumpeter, 1911; Romer, 1986; Aghion and Howitt, 1992). In particular, corporate innovation is a key determinant of firms' long-term profit growth (Arrow, 1962).

Firms usually invest in R&D and develop technologies to employ them in their production. However, due to the uncertain nature of their R&D processes, they also obtain patents for some inventions that they decide not to commercialize. For instance, an innovation may turn out to be less useful for the firms' core business activity (Akcigit et al., 2016), or the firms may lack the necessary complementary assets to benefit from employing the innovation (Teece, 1986; Arora and Ceccagnoli, 2006). As a result, firms may seek alternative ways to profit from these patents.

Some of these technologies can benefit other firms. Consequently, the innovators can profit from selling their intellectual property rights to potential adopters of the technology. Serrano (2010) finds that 13.5% of all patents granted by the USPTO are traded at least once over their life cycle. This statistic indicates that the market for patents is an essential factor for inventing firms to profit from their innovations. Furthermore, a well-functioning market for technology improves the allocation of technological knowledge and property rights to use this knowledge commercially. Akcigit et al. (2016) estimate that compared to the status quo, an increase in the efficiency of the market for ideas could result in a welfare gain up to 17.8%.

However, technology transfer is often hampered by the presence of information asymmetries between sellers and buyers. A technology transfer consists of both trading of intellectual property rights and also transferring of innovative know-how. This specialized know-how facilitates the application of new technologies. It is generally not fully revealed in the patents and, thus, is private knowledge of the inventing firm (Arora, 1995). Ensuring that the buyer gains the full benefit of its adoption requires that the seller of the technology has an incentive to transfer the uncodified know-how (Macho-Stadler et al., 1996).

In this paper, I explore, theoretically and empirically, whether the presence of common institutional owners can help ease the information frictions in the market for ideas. Specifically, I study whether firms that share common institutional shareholders with a potential adopter have more incentives to reveal valuable information making the reallocation of technology more beneficial for the acquirer. The market for technological knowledge is an understudied area, especially in its relationship with the financial markets.

I present a simple model of technology transfer in which an innovator can sell its intellectual property rights to potential buyers who benefit when adopting the innovation.[1] I study the factors that determine the reallocation of the technology in the equilibrium of a sequential game. In particular, I analyze how common ownership affects the selection of the acquirer. Common owners, seeking to maximize the value of their portfolios, provide incentives to the firms' managers to internalize the effect of their decisions on the other firms.

In the case of symmetric information and the absence of business stealing effects among potential adopters, I show that common ownership has no impact on the allocation of technologies. At equilibrium, the only determinant of the identity of the actual acquirer is its increase in profits thanks to the new technology. For instance, the buyer's technological propinquity is an essential factor for its selection.

Then, I study the more realistic scenario where the transfer of know-how from the technology provider to the selected buyer is unverifiable. I show that common ownership alleviates the moral hazard problem in know-how transfer. The larger the overlap in ownership, the stronger the incentives provided to the seller's manager to internalize the buyer's profit, and the more know-how is transferred to the acquirer. Through this mechanism, the value of a deal increases with the ownership overlap between the innovator and the potential acquirer. As a consequence, the likelihood that the technology is transferred to a particular firm increases with the level of common ownership between the seller and this firm.

The empirical part uses USPTO patent reassignment data and different sets of common ownership measures to provide evidence on the effect of common ownership incentives on technology transfer. I construct a unique sample on the firm pair level merging information from different data sources using a name-matching algorithm. I carefully identify traders in the market for technology and match these firm pairs with control groups of firm pairs consisting of the actual technology provider and counterfactual acquirers in the same sector as the true adopter of the technology. I use this sample to estimate (using probit and conditional logit regressions) the relationship between common ownership and the probability

[1] Although my model focuses on patent trades, the mechanism I describe also applies to other forms of technology transfer, such as licensing.

that a firm pair engages in technology transfer controlling for the technological propinquity of the potential acquirers and a large set of firm and industry controls usual in studies on corporate innovation in financial economics.

The results from the probit and conditional logit regressions may be biased due to unobservable characteristics driving both technology transfer and common ownership. To address the issues of omitted variable bias and reverse causality, I employ different strategies to identify the causal effect of common ownership.

First, a potential concern is that more innovative firms tend to engage more in technology transfer and may at the same time attract more institutional investment. This correlation could lead to a spurious relationship between common ownership and the probability of technology transfer. For this reason, I control for firms' innovativeness by including measures of firms' R&D intensity and their long-term innovativeness, which I construct from information on R&D expenses and past patent applications.

Second, to control further for unobservable characteristics, I construct matched samples to select a subset of the control observations. For robustness, I employ two different matching techniques. Namely, I perform a propensity score matching to select those control pairs that are similarly likely to engage in technology transfer as the actual traders based on their most relevant characteristics, other than common ownership. Since propensity score matching may increase imbalances of the sample by pruning observations, I confirm my results using a Mahalanobis distance matching (King and Nielsen, 2019).

Third, to additionally address the concern of reverse causality, I employ an instrumental variable strategy based on the trading partners' pairwise stock market index membership to estimate the causal effect of common ownership. The idea behind this instrument is that some institutional investors benchmark their funds against the performance of stock market indices such as the *S&P500* and the *Russell1000*. They track an index by investing in its constituents. Therefore, if two firms are included in the same stock market index, they are more likely to have these institutional investors as common owners (Newham et al., 2019; Gilje et al., 2020). Thus, pairwise inclusion in a stock market index increases common ownership for reasons unrelated to technology transfer. I use this exogenous variation instrumenting my common ownership measures to establish causality.

I confirm that common ownership of investors increases the probability that two firms engage in technology transfer. Importantly, I also show that this effect is stronger for complex technologies, for which the transfer of the know-how is more likely to substantially influence profits. These results suggest that the alleviation of moral hazard in know-how transfer is a plausible mechanism through which common owners facilitate technology transfer and, therefore, affect the reallocation of technologies and innovative knowledge.

My paper contributes to the recent debate on the influence of institutional investors' common ownership on firm behavior. Institutional investment has been on the rise during the last four decades.[2] Since institutional investors usually hold diversified portfolios, this

[2]For instance, the average share of stocks of S&P500 corporations held by institutional owners has more

increase in institutional investment goes hand in hand with tremendous increases in the overlap of firms' shareholders.[3] As in other contributions to this debate, I show that common ownership has a significant impact on firm behavior. However, despite the anti-competitive effects and potential remedies discussed in the literature, my results show that common ownership may facilitate the reallocation of technology and the dissemination of technological know-how in the economy and, thus, may contribute to the functioning of the market for ideas.

The remainder of the paper is organized as follows. Section 2.2 relates my paper to the existing body of literature. The model is presented in section 2.3. In particular, section 2.3.1 discusses the influence of common ownership on the objective functions of firms. In section 2.3.2, I solve the model under symmetric information. Section 2.3.3 introduces the moral hazard problem in transferring unverifiable know-how and analyzes the consequences for the allocation of the technology and the impact of common ownership. Motivated by my model, I develop testable hypotheses. Section 2.4 describes the data and variables used in the empirical analysis, and section 2.5 discusses the construction of the samples and presents descriptive statistics. The empirical strategy is outlined in section 2.6. Section 2.7 contains the results. Finally, section 2.8 concludes.

2.2 Related Literature

My paper relates to different strands of literature. First, it relates to the literature on the incentives and contracts in technology transfer (Gallini, 1984; Katz and Shapiro, 1985; Shapiro, 1985; Gallini and Wright, 1990; Macho-Stadler et al., 1996; Duchêne et al., 2015) and, in particular, to the papers on patent reassignments (Serrano, 2010; Akcigit et al., 2016; Serrano, 2018; Figueroa and Serrano, 2019; Kwon et al., 2021). A closely related paper by Arqué-Castells and Spulber (2021) studies the impact of business stealing effects on the matching of firms in the market for technology.

Second, my paper contributes to the recent discussion on the influence of institutional common ownership on the behavior of publicly traded companies. Scholars and policy makers alike have been concerned about the potential anti-competitive effects of common ownership (Azar, 2017; OECD, 2017; Azar et al., 2018, 2019; Frazzani et al., 2020) and possible solutions have been proposed (Elhauge, 2016; Baker, 2016). To which extent institutional investors with overlapping ownership stakes influence firms' product market strategies like output and prices is an ongoing debate (Kennedy et al., 2017; Dennis et al., 2019; Azar et al., 2021; Backus et al., 2021).

Research has shown that common ownership could have different important implications, e.g., for managerial incentives (Antón et al., 2021b), acquisitions (Matvos and Ostro-

than doubled during this period reaching above 80% in 2017 (Backus et al., 2019).

[3] According to He and Huang (2017), the share of firms in the same four-digit SIC industry that have at least one institutional blockholder in common has on average increased from under 10% in 1980 to around 60% in 2014.

vsky, 2008; Harford et al., 2011; Brooks et al., 2018; Antón et al., 2021a), governance (He et al., 2019), within-industry cooperation (He and Huang, 2017), and firm entry (Newham et al., 2019). I add to this literature by analyzing the influence of common ownership in the market for technology showing that the overlap in firms' shareholders has a positive effect on the quality of the technology transfer and the selection of patent assignees.

Third, using different measures of common ownership in my analysis, my paper also contributes to the debate on how much common owners' preferences are internalized by firms' management and, therefore, change actual firm behavior. Gilje et al. (2020) provide a model of managerial incentives to internalize common ownership of the shareholders in publicly traded companies. They emphasize the role of investor inattention, limiting the extent to which common ownership influences managers' decision-making and, therefore, firm behavior. From this model, they derive a firm-pair measure of managerial common ownership incentives, the GGL measure. There is ample evidence confirming that the portfolio weight, i.e., the fraction that an institution's investment in a firm takes in the investor's portfolio, matters for the degree to which the investor monitors the firm and to which extent this monitoring impacts actual firm behavior.[4] Motivated by this evidence Gilje et al. (2020) assume that the probability that an investor is attentive to managerial decisions increases in the portfolio weight.

Gilje et al. (2020) also replicate the findings of Azar et al. (2018) on the positive relationship of common ownership on the average fare charged by airlines on different routes in the US. However, using their GGL measure instead of the MHHI*delta* used in Azar et al. (2018), Gilje et al. (2020) do not find any significant effect of common ownership on ticket prices. In my paper, I provide evidence that using the GGL measures, common ownership incentives influence firm behavior in the market for technology.

Finally, my analysis also contributes to the theoretical literature on common ownership (Rotemberg, 1984; Azar, 2017) and its relationship with corporate innovation (López and Vives, 2019; Vives, 2020; Antón et al., 2021c). My paper differs from these articles by considering endogenous know-how transfers rather than exogenous knowledge spillovers. My model makes explicit which role information asymmetries play for the relationship between common ownership and the matching of firms. I model how common ownership alleviates the difficulties for these partners of the deal that are caused by asymmetric information as first mentioned by He and Huang (2017). Due to the common ownership incentives, the decision of the assignor concerning the transfer of know-how determines the value of the match and, therefore, common ownership incentives affect the equilibrium matching.

[4]For evidence on the importance of the portfolio weight of a firm in the investors portfolio see, for instance, Iliev and Lowry (2015), Fich et al. (2015), Ward et al. (2018), and Iliev et al. (2020).

2.3 The Model and Hypothesis Development

In this section, I present a model in which the owner of a technology (the assignor) can sell this technology (patents) to two potential buyers (assignees). Let firm 0 be the initial owner of the technology. I assume that it cannot benefit from applying it, for example, because it is far from his core line of business as in Akcigit et al. (2016), or because it lacks the necessary complementary assets and the access to these assets is restricted (Teece, 1986; Arora and Ceccagnoli, 2006). On the other hand, firms 1 and 2 are the potential adopters of the technology codified in firm 0's patents and can benefit from obtaining exclusive rights to use it.

Let π_l be the operational profits of firm l, $l = 1, 2$. I denote the ex-ante operational profits of firm l by $\tilde{\pi}_l$, i.e., $\tilde{\pi}_l$ represents the profits of firm l if it does not adopt the technology. In case firm l becomes the assignee and adopts the technology, it makes a higher operational profit π_l^r, i.e., $\pi_l^r > \tilde{\pi}_l$. In case its rival in the market for technology buys the patents and adopts the technology, firm l continuous to operate with its old technology and earns profits $\tilde{\pi}_l$. Thus, I assume for now that there are no business stealing effects between the potential adopters, i.e., the adoption of the technology by one potential assignee does not hurt the other. Later, I will discuss what changes if we relax this assumption.

The extent to which a firm can benefit from applying the technology may depend, for instance, on the technological propinquity between the reassigned technology and the firm's location in the technology space. Thus, π_l^r may depend on firm l's experience in the technological field and the usefulness of the technology for its core business activity.[5]

Furthermore, I assume that there is no product-market rivalry between the assignor and the potential assignees. Thus, the operational profits of the assignor in its core business activities are unaffected by the transfer of technology and can be ignored in the model.[6] This assumption simplifies the analysis and helps understand the direct impact of common ownership on the selection of the assignee in the subsequent analysis of the model. Then, I normalize firm 0's operational profits if it keeps the technology to zero.

A technology transfer contract reassigns the intellectual property rights of the technology from the assignor (firm 0) to the assignee (either firm 1 or 2). It also stipulates a fixed fee payment $F \geq 0$ paid by the assignee to firm 0. Thus, I do not consider contracts including royalty payments. Contracts that exclusively contain lump-sum payments for the provision of intellectual property rights seem to be common in the market for technology.[7] Moreover, they are efficient in the absence of product market competition and

[5] I will use the notion of technological distance in my empirical analysis to gauge an assignee's capacity to benefit from applying a particular technology.

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

[7] In a study on patent assertion entities, the FTC (Federal Trade Commission, 2016) collected confidential business information on licensing contracts executing its authority under Section 6(b) of the Federal Trade Commission Act. It reports that 83.7% of licensing contracts only include lump-sum payments, while 13.5% of contracts include only running royalties. In the case of 2.8% the contracts included both fixed

asymmetric information between the seller and the buyer since a fixed fee does not distort an adopter's product-market strategy. All my qualitative results would remain if we allowed for the possibility of royalties.[8] Finally, if firm 0 reassigns the technology, it incurs a cost of technology transfer $C \geq 0$.

Having described the contract F, the cost of technology transfer C, and the operational profits of the potential adopters π_l, I define the firms' net profit functions. Firm 0's net profits in case it reassigns the technology to firm l are the difference between the fixed payment and the cost of the technology transfer, i.e., $\Pi_0 = F - C$ (remember that I have normalized its profits to zero if it keeps the technology).

The potential adopters earn net profits denoted by Π_l, for $l = 1, 2$. If firm 0 keeps the technology, firm l's net profits coincide with the ex-ante operational profits and $\Pi_l = \tilde{\pi}_l$. If, however, one of the potential adopters, say firm 1, makes a deal with firm 0, it earns net profits $\Pi_1 = \pi_1^r - F$, while the other potential assignee, say firm 2, earns net profits $\Pi_2 = \tilde{\pi}_2$, and vice versa.

I analyze the transfer of the technology as a sequential game. The timing of this game is the following. At the first stage, which I denote by S_1, firm 0 decides whether to reassign the technology. In case it does, it determines which potential adopter to approach first and the fixed fee requested. I call firm α the potential adopter of the technology that firm 0 approaches first. Then, firm α decides whether to accept or reject the contract. If firm α accepts the contract, the technology transfer occurs, and the fixed fee F is paid to firm 0. In this case, the game ends. Otherwise, we move to the stage S_2, where firm 0 decides whether to offer the technology to the other potential adopter, which I call firm β. If firm 0 chooses to offer a contract to firm β, it determines the fixed fee. Finally, firm β accepts or rejects the offer, and profits are realized.

In the subsequent analysis, I apply the solution concept of subgame perfect equilibrium and solve the game by backward induction. However, before I analyze the game, I describe how common ownership influences a manager's decisions in the following section.

2.3.1 Common ownership incentives

In Industrial Economics in general and in papers on technology transfer in particular, it is standard to assume that the profit function of a firm is the objective function of the

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and royalty payments. In the case of patent reassignments in which the ownership of patents changes, the use of lump-sum payments is expectedly even more pervasive. In a sample of Spanish technology adopters, Macho-Stadler et al. (1996) show that in case the technology transfer involves a transfer of property rights, a higher share of contracts involves predominantly fixed fee payments compared to deals that involve only the transfer of use or commercial rights. Variable royalty payments that depend on the use of the technology or the sales of the assignee associated with the application of the patents would require permanent monitoring by the assignor, which is costly.

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

agents that take decisions on behalf of the firm and, therefore, choose the firm's strategy. Thus, firms act as profit maximizers in these models. This assumption is motivated by the reasoning that a firm's owners can incentivize managers to work in their best interest. It relies on the underlying assumption that owners want the firm's managers to maximize its profits.

On the contrary, the Common Ownership Hypothesis states that investors that hold shares in various firms maximize the value of their portfolio, which might induce firm behavior that departs from profit maximization (Schmalz, 2018; Backus et al., 2020). Rather than behaving as independent profit maximizers, firms act as if being part of a larger corporate structure. How the objective of common owners translates into managers' incentives and, therefore, changes firm behavior has been studied in recent years. Azar (2017) and Gilje et al. (2020) propose different models in which common owners induce managers to internalize the effect of their decisions on portfolio firms through their voting in annual meetings. Antón et al. (2021b) show that common ownership affects the incentives provided by the compensation contracts to managers.

In my model, I abstract from the concrete mechanism that leads managers to take into account the common owners' interests. Instead, I assume that such a mechanism exists and that its strength depends on the extent of common owners' shares in the different firms.

Suppose, there is a set of investors $i = 1, ..., I$. Each investor can hold shares in several companies. Following Rotemberg (1984), Azar (2017), and López and Vives (2019),[9] I assume that firm 0's management maximizes a weighted average of its shareholders' wealth. A subset of firm 0's shareholders also invest in firm $l = 1, 2$. As shown by López and Vives (2019), this leads to the following objective function[10]

$$\phi_0 = \Pi_0 + \lambda_{01}\Pi_1 + \lambda_{02}\Pi_2, \tag{2.1}$$

where λ_{0l} is the profit weight that the management of firm 0 puts on the profits of firm l in its objective function. By definition, $\lambda_{00} = 1$, that is, the weights that the management puts on the other firms are measured relative to firm 0's profits. Therefore, firm 0 behaves as if it would maximize the sum of own profits and a weighted sum of the other firms' profits.

[9] See López and Vives (2019) for a discussion on how different arrangements of overlapping ownership structures may influence how firms internalize the profits of rivals. See also O'Brien and Salop (2000).

[10] This objective function can be easily derived. Let the share hold by investor i in company $j \in \{0, 1, 2\}$ be denoted by $\beta_{ij} \in [0, 1]$ with $\sum_i \beta_{ij} = 1$ and let investor i's wealth be given by $W_i = \sum_j \beta_{ij}\Pi_j$, $i = 1, ..., I$. Assume that the manager of firm 0 maximizes a weighted sum of inverstors' wealth, i.e.,

$$\sum_i \gamma_{i0} W_i,$$

where γ_{i0} are Pareto weights that the manager of firm 0 assigns to investor i. This maximization problem yields the same solution as (2.1) with $\lambda_{0l} \equiv (\sum_i \gamma_{i0}\beta_{il})/(\sum_i \gamma_{i0}\beta_{i0})$, $l = 1, 2$. See the Appendix A.1 for a detailed derivation.

2.3.2 Technology Transfer under Common Ownership and Symmetric Information

In this section, I analyze the equilibrium of the technology-transfer game and, in particular, the role of common ownership incentives of the technology provider (as described in section 2.3.1) in the basic model outlined in section 2.3 above. Here, I assume that there is no moral hazard in the provision of the technology, i.e., each potential adopter can sign a contract with the technology provider in which the provision of technology is verifiable. In other words, there are no information asymmetries between the parties.

I assume that firm 0 internalizes the preferences of its owners as described in equation (2.1). Therefore, it has common ownership incentives $\lambda_{0l} \in [0,1]$ with respect to each potential assignee $l \in \{1,2\}$.

I solve the model by backward induction. Consider the state where firm α was offered the contract at the first stage of the game S_1 and it rejected the offer. At stage S_2, firm 0 can offer the technology to the second adopter, firm β. In case it decides to do so, it chooses the fee F^{S_2} in order to maximize (2.1). Then, firm 0's objective function at stage S_2 is the following

$$\phi_0(F^{S_2}) = F^{S_2} - C + \lambda_{0\alpha}\tilde{\pi}_\alpha + \lambda_{0\beta}(\pi^r_\beta - F^{S_2}). \tag{2.2}$$

Notice that $\phi_0(F^{S_2})$ increases in F^{S_2} for all $\lambda_{0\beta} \in [0,1)$.

Firm β accepts any offer if its profits are higher than its outside option $\tilde{\pi}_\beta$, that is, if $F^{S_2} \leq \pi^r_\beta - \tilde{\pi}_\beta$. Firm 0 has an incentive to set F^{S_2} as high as possible. Hence, if it decides to transfer, it will offer $F^{S_2} = \pi^r_\beta - \tilde{\pi}_\beta$.[11] Therefore, firm 0 finds it profitable to transfer the technology to firm β if $\pi^r_\beta - \tilde{\pi}_\beta \geq C$, and keeps the technology otherwise.

Going backwards, assume that firm 0 approaches firm α at stage S_1 and determines the contract F^{S_1}. Firm α's profits when accepting the contract are $\mathit{\Pi}_\alpha = \pi^r_\alpha - F^{S_1}$. Its outside option is $\tilde{\pi}_\alpha$. Firm 0's profits increase with F^{S_1}. Thus, its optimal contract for firm α is

$$F^{S_1} = \mathit{\Delta}\pi_\alpha \equiv \pi^r_\alpha - \tilde{\pi}_\alpha. \tag{2.3}$$

Firm 0 finds it indeed profitable to make an offer to firm α whenever

$$\phi_0(F^{S_1}) \equiv \mathit{\Delta}\pi_\alpha - C + \lambda_{0\alpha}(\pi^r_\alpha - \mathit{\Delta}\pi_\alpha) + \lambda_{0\beta}\tilde{\pi}_\beta \geq \tilde{\phi}_0, \tag{2.4}$$

where $\tilde{\phi}_0 \equiv \lambda_{0\alpha}\tilde{\pi}_\alpha + \lambda_{0\beta}\tilde{\pi}_\beta$ is firm 0's ex-ante value of its objective function. From now on, I assume that (2.4) holds for at least one firm, i.e., $\phi_0(F^{S_1}_l) \geq \tilde{\phi}_0$ for some $l = 1, 2$. Otherwise no technology transfer takes place.

[11] In this section, I analyze the model under the assumption that firm 0 has all the bargaining power when offering a contract to a potential adopter. This is plausible since it is the owner of a unique technology (i.e., a bundle of patents) and, therefore, is a monopolist. In Appendix A.2, I show that my results are robust to this assumption, analyzing a two-sided matching model with contracts.

Given that technology transfer is profitable, firm 0 decides the identity of the first assignee by solving the following problem

$$\max\left\{\phi_0(F_1^{S_1}), \phi_0(F_2^{S_1})\right\}. \tag{2.5}$$

Taking stock of what we have learned, I state the first result in the following lemma and proposition.

Lemma 1. *Suppose that firm 0 wants to sell the technology in equilibrium, i.e., $\phi_0(\Delta\pi_l) \geq \tilde{\phi}_0$ for at least some $l = 1, 2$. Then, firm 0 sells the technology to firm 1 if and only if $\Delta\pi_1 \geq \Delta\pi_2$. In this case, the fixed fee is $F = \Delta\pi_1$.*[12]

Proof. The proof is straightforward since $\phi_0(F_1) \geq \phi_0(F_2)$ is equivalent to $\Delta\pi_1 \geq \Delta\pi_2$. □

Proposition 1 is an immediate consequence of Lemma 1.

Proposition 1. *The selection of the assignee is independent of the strength of common ownership incentives.*

Intuitively, if firm 0 can extract all the rents from the technology transfer, then the increase in the adopter's net profit from buying the technology is zero, i.e., $\Delta\pi_l - F_l = 0$, for each potential assignee. Moreover, the reassignment does not hurt the non-assignee. Therefore, firm 0 is only concerned by the fixed fee F it receives. Thus, the common ownership incentives do not influence to which firm the assignor transfers the technology. The only determinant that makes firm 0 choose one assignee over the other is that the first can profit more from applying the technology than the latter and, thus, firm 0 can earn a higher profit by selling to this firm.

The underlying assumption that leads to a fixed fee $F_l = \Delta\pi_l$, extracting all the rents from the technology transfer, is that the technology provider has all the bargaining power when proposing the contract. This assumption is plausible since the provider is a supplier of a unique good, i.e., the concrete bundle of patents, and, therefore, acts as a monopolist. In section A.2 of the Appendix, I relax the assumption that the provider has all the bargaining power. I show in a simple model of a two-sided matching market with contracts that the main result derived in this section (Proposition 1) holds for any distribution of bargaining power between the provider and the adopters. The reason is that the firm that benefits the most from adopting the technology is always able to compensate the provider by paying a fixed fee that is at least as high as the provider's benefit when selling to the other firm. Thus, the firm with the highest increment in profits due to the technology $\Delta\pi_l$ always becomes the assignee, and the distribution of bargaining power does not affect the equilibrium allocation of the technology. It only influences the amount F payed to the provider. Hence, the impact of common ownership remains to be nil.

[12] I assume, without loss of generality, that if the technology provider is indifferent between the two firms, firm 1 is always chosen.

I also have assumed that a potential adopter is not affected by the technology transfer to another firm. Here, I briefly discuss the case in which I relax this assumption. For a detailed discussion, see section A.3 in the Appendix.

Consider the environments where there are business stealing effects between the potential assignees. Business stealing effects are relevant, for instance, if the two firms produce similar products. The technology adopter benefits from the transfer and gains a competitive advantage over the outsider of the deal. Hence, I assume that the outsider is hurt if the other firm adopts the technology. Therefore, the outsider earns operational profits π_l^n, for $l = 1, 2$, which is less than its ex-ante operational profits, i.e., $\pi_l^n < \tilde{\pi}_l$.

In this case, the technology provider can ask a potential adopter at stage S_1 for a higher fixed fee compared to the environment without business stealing when it is profitable to sell to the other firm at stage S_2. The reason is that the outside option of the adopter decreases from $\tilde{\pi}_l$ to π_l^n if selling to the rival is profitable. Furthermore, the provider takes into account the business stealing effect on a firm with which it has common owners when deciding to sell to its rival. For example, suppose firm 0 wants to sell the technology to firm 2 (with which it may have common owners or not). If firm 0 has common owners with firm 1, it partially internalizes this business stealing effect on firm 1, which acts as a cost for the technology provider, reducing the deal's value when selling to firm 2. As common ownership between firms 0 and 1 increases, firm 0 finds it less attractive to trade with firm 2, and it may decide to sell to firm 1 instead. Therefore, common ownership can make it more likely that a firm becomes the assignee unless the business stealing effects are very large. Consequently, we may observe a positive relationship between common ownership and the probability that two firms will transfer technology with moderate business stealing effects.[13]

To sum up the preceding sections, first, common ownership does not affect the selection of the adopter in equilibrium if there are no business stealing effects between potential adopters. Second, common ownership can positively affect the choice of a particular adopter if business stealing effects are not too strong. In the proceeding analysis, I will abstract from business stealing effects between potential adopters since this simplifies the analysis without much loss of generality to show the consequences of the existence of moral hazard regarding know-how transfer.

2.3.3 Technology Transfer under Common Ownership and Moral Hazard

In this section, I study environments where the transfer of the technology is not fully verifiable. The technology provider, firm 0, transfers a patent, or a bundle of patents; but, he can also transfer an unverifiable component of the technology, i.e., know-how. Thus, the know-how transfer is subject to moral hazard. This know-how can help the technology

[13]To show this result, it is sufficient that the business stealing effects are not larger than the social benefit from selling to the other firm. Otherwise, there exists a non-monotonic relationship. For details, see section A.3 in the Appendix.

adopter to increase the profitability of implementing the reassigned technology. Indeed, innovators that sell a technology often possess specialized know-how that is useful for adopting the technology. The adopter relies on the transfer of this know-how to leverage the full potential of the technology. This know-how is not codified in the patents and, therefore, the transmission of know-how is a separate and costly action. Only the owner of the patents can use the specialized know-how.

I denote the amount of know-how transferred as $k_l \geq 0$. Then, π_l^r is a function of k_l, the know-how transferred to firm l together with the intellectual property. Denote $\mathit{\Delta}_l$ the increase in firm l's profits if $k = 0$. I make the following two assumptions.

Assumption 1. *If firm 0 reassigns the technology to firm l, then the ex-post profit of firm l increases linearly in know-how transfer,*[14] *i.e.,* $\pi_l^r = \tilde{\pi}_l + \mathit{\Delta}_l + \gamma k_l$.

Assumption 2. *If firm 0 transfers an amount k_l of know-how it incurs a cost of* $C(k_l) = \frac{1}{2}\nu k_l^2$.

The timing of the game is the same as before. However, firm 0 also has to decide how much know-how to transfer. It does so after some firm $l = 1, 2$ has accepted the proposed contract at stage S_1 or S_2 of the game.

Since there are no business stealing effects ($\pi_l^n = \tilde{\pi}_l$), the increase in operational profits of firm $l = 1, 2$ if the know-how transferred is k_l is $\mathit{\Delta}\pi_l(k_l) = \pi_l^r(k_l) - \tilde{\pi}_l$ if it becomes the assignee. Furthermore, it is easy to check that the participation constraint of the assignee has to be binding, and the optimal contract is, therefore, $F_l = \mathit{\Delta}\pi_l(k_l)$. However, firm 0 must have the incentives to transfer the expected amount of know-how after the contract is signed. That is, the following Incentive Compatibility Constraint (ICC) must hold:

$$k_l = \arg\max_{\hat{k}_l} F_l + \lambda_{0l}\left[(\mathit{\Delta}_l + \gamma \hat{k}_l) - F_l\right] - \frac{1}{2}\nu \hat{k}_l^2. \tag{2.6}$$

From the ICC follows that, independently of the fixed fee, firm 0 will credibly transfer to firm l an amount of know-how

$$k_l = \frac{\gamma}{\nu}\lambda_{0l} \tag{2.7}$$

after the contract is signed. From (2.7), we see that more know-how is transferred to an assignee if the common ownership incentive λ_{0l} is higher since firm 0's manager internalizes the effect of the transferred know-how on the assignee's profits. Moreover, the assignor transfers more know-how if, given λ_{0l}, know-how is more productive in the adoption of the technology (higher γ) or the know-how transfer is less costly (lower ν). Using the

[14] Since k_l is not verifiable we can assume that $\pi_l^r = \tilde{\pi}_l + \mathit{\Delta}_l + \gamma k_l + \epsilon_l$, where $\epsilon_l \sim \mathcal{N}(0, \sigma_l^2)$, such that k_l cannot be inferred from the assignee's profit. Since all firms are assumed to be risk-neutral they maximize the expected value of (a linear combination of) profits and, therefore, adding noise does not change the analysis.

participation constraints of the potential assignees and the ICC (2.7), we can derive the fixed fee in the optimal contract firm 0 can offer to each potential assignee, i.e.,

$$F_l = \Delta\pi_l = \Delta_l + \frac{\gamma^2}{\nu}\lambda_{0l}. \tag{2.8}$$

The profit firm 0 can make from transferring the technology to firm l is the difference between the fixed payment and the cost of know-how transfer, i.e.,

$$\Pi_0 = F_l - \frac{1}{2}\nu k_l^2 = \Delta_l + \lambda_{0l}\left(1 - \frac{1}{2}\lambda_{0l}\right)\frac{\gamma^2}{\nu}. \tag{2.9}$$

Notice, that the ex-post net profits of both assignees equal their ex-ante profits, i.e., $\Pi_l = \tilde{\pi}_l$, whether or not they adopt the technology. Therefore, the problem of firm 0 that determines the choice of the assignee is

$$\max\left\{\Delta_1 + \lambda_{01}\left(1 - \frac{1}{2}\lambda_{01}\right)\frac{\gamma^2}{\nu}, \Delta_2 + \lambda_{02}\left(1 - \frac{1}{2}\lambda_{02}\right)\frac{\gamma^2}{\nu}\right\}. \tag{2.10}$$

I state the result of this game in the following proposition.

Proposition 2. *Let $\lambda_{01} \geq \lambda_{02}$. Firm 0 assigns the patents to firm 1 if*

1. $\Delta_1 \geq \Delta_2$, *or*
2. $\Delta_1 < \Delta_2$ *and* $\lambda_{01} \geq \bar{\lambda}_{01}(\Delta_1, \Delta_1, \lambda_{02})$,

where $\bar{\lambda}_{01}(\Delta_1, \Delta_1, \lambda_{02}) = 1 - \sqrt{1 - 2\frac{\nu}{\gamma^2}(\Delta_2 - \Delta_1) - 2\lambda_{02}(1 - \frac{1}{2}\lambda_{02})}$.

Proof. See Appendix (section A.4). □

Intuitively, if $\lambda_{01} \geq \lambda_{02}$ and firm 1 has at least the same potential to profit from adopting the technology than firm 2, i.e., $\Delta_1 \geq \Delta_2$, the assignor always prefers to sell the technology to firm 1 because the incentives from common ownership lead firm 0 to transfer more know-how after the contract is signed. Since the assignor can, therefore, promise to share more know-how and this promise is credible, he can extract more profits from the assignee with higher common ownership.

If firm 2 has an initial technological advantage, i.e., $\Delta_2 > \Delta_1$, the technology is still assigned to firm 1 if the common ownership incentives are sufficiently large compared to the common ownership incentives with regard to firm 2. If the common ownership incentives are strong with regard to firm 1 compared to firm 2, the higher know-how transfer to firm 1 can make up for its technological disadvantage.

To see the effect of common ownership on the probability that firm 1 becomes the assignee, I denote $\Lambda_l \equiv \lambda_{0l} - \frac{1}{2}\lambda_{0l}^2$, which is an increasing function of λ_{0l} for all $\lambda_{0l} < 1$. Then, firm 0 sells to firm 1 whenever the following condition holds:

$$\Lambda_1 - \Lambda_2 \geq \frac{\nu}{\gamma^2}(\Delta_2 - \Delta_1). \tag{2.11}$$

Suppose that $\varDelta_2 > \varDelta_1$, i.e., firm 2 has an initial technological advantage. Then, the right-hand side of (2.11) is positive. Therefore, firm 1 can only become the assignee if firm 0 internalizes the effect of know-how transfer on firm 1's profits to a sufficiently larger extent compared to firm 2. We also see from (2.11) that the condition gets stricter if the efficiency gain from know-how transfer decreases, i.e., as either know-how transfer becomes more costly for firm 0 (higher ν) or the productivity of know-how decreases (lower γ). On the contrary, if the profit of the assignee depends strongly on the know-how transferred, i.e., γ is large, the effect of common ownership on the reallocation becomes more relevant, i.e., the impact of common ownership on the allocation of the technology becomes more substantial. I summarize the results of this section in the following proposition.

Proposition 3. *(a) If there is a moral hazard problem due to unverifiable know-how in the transfer of the technology, then common ownership increases the probability that a firm becomes the assignee in equilibrium. (b) The effect of common ownership on the allocation of the technology is stronger if the transfer of know-how is more crucial for the adoption of the technology.*

We have seen that moral hazard in the transfer of unverifiable know-how leads to a positive relationship between common ownership and the probability of technology transfer to an assignee. This effect of common ownership on the selection of the assignee was absent in the case of technology transfer without unverifiable know-how in section 2.3.2 (Proposition 1). Therefore, in the empirical part of this paper I will test the following hypothesis.

Hypothesis 1. *The higher the common ownership between the assignor and a potential assignee, the higher is the probability of engaging in technology transfer for the firm pair.*

We also have seen that a primary determinant for the selection of the assignee is its capability to profit from the technology it adopts. In the model, this corresponds to $\varDelta\pi_l$ in section 2.3.2 and, in the current section, to $\varDelta_l$, i.e., firm l's technological capability to profit from adopting the technology independent from the transfer of the unverifiable component. A proxy for this capability is a firm's technological proximity to the reassigned technology. Akcigit et al. (2016) find that a patent contributes more to a firm's stock market value the closer it is to the firm in technological terms. That is, the closer the patent is to the firm's patent stock. Kwon et al. (2021) show that it is more likely that firms engage in a patent trade if the patent is relatively closer to the patent stock of the buyer than to the initial owner's patent stock. Therefore, I expect firms' technological proximity to the reassigned technology to be crucial for selecting the assignee and test the following hypothesis.

Hypothesis 2. *The probability that a potential assignee is selected to engage in technology transfer decreases with the technological distance of its patent stock to the reassigned technology.*

Furthermore, we have seen that the impact of common ownership is more substantial if the agency problem is more severe. Since common ownership provides incentives to the technology provider's management to transfer know-how, the effect on the assignee selection should be stronger if this know-how is more crucial for the adoption of the technology as stated in Proposition 3. Technologies differ in their requirement of the provision of specialized know-how by their initial owners. Simple technologies may not require the transfer of know-how at all. In contrast, the adoption of more complex technologies depends on the instruction of the initial owner so that their productivity can be fully exploited (Macho-Stadler et al., 1996). A complex innovation combines novel know-how from many different technological areas. This know-how, not codified in the individual patents of the bundle that comprises the intellectual property of this technology, is not accessible for the assignee without the transfer of the know-how by the technology provider. Thus, the positive effect of common ownership on the selection of the assignee should be stronger for complex technologies if the moral hazard problem in know-how transfer is a crucial issue. Therefore, I test the following third hypothesis.

Hypothesis 3. *The effect of common ownership on the assignee selection is stronger if the reassigned technology is more complex.*

2.4 Data and Variables

I now describe the data sources used to construct the sample and the variables I constructed. I first outline the process of merging the different data sets used in my analysis.

2.4.1 Data

I construct the sample based on information of US public firms for the period 1990 to 2006. First, I retrieve financial information for all the companies in Compustat, excluding financial and utilities firms (standard industrial classification (SIC) codes between 4000 and 4999 and between 6000 and 6999) and merge these data with information from several other databases.

I obtain information on patent reassignments from the USPTO Patent Assignment Dataset. This data set contains the names of the assignors and assignees that engaged in a transfer of ownership of patents. I clean this data set extensively to obtain reassignment information that indicates real changes in ownership of patents. I eliminate reassignments due to name changes, mergers, employee assignments, or other reasons unrelated to technology transfer between firms.

Following Akcigit et al. (2016), I use an algorithm to clean the names of the parties involved in the reassignments. Next, I apply the same name cleaning algorithm to the company names in Compustat. After that, I match firms between the reassignment data set and Compustat using a fuzzy matching algorithm (the *matchit* function for stata).

Finally, I manually check all matches and compared them with company information from Google to obtain a data set that only includes matched firms where the firm's identity is the same in the two data sets.

Thomson Reuters Institutional Holdings 13F database provides institutional ownership information. This data set is used to construct the main explanatory variables, i.e., the measures of common ownership. For 1990 to 2006, I collect information concerning the number of outstanding shares, the share prices, and the shares held by institutional investors in a given firm. The 13F data set suffers from several data quality issues. Therefore, I manually clean the data from duplicate observations, incorrectly assigned holdings information, and replace missing information. In particular, I supplement the information with the Center for Research in Security Prices (CRSP) data for missing values on the end-of-quarter stock price and outstanding shares. After cleaning the data, I aggregate fund holdings at the institutional investor level.[15]

I obtain R&D expenses from Compustat and collect patent and citation information to construct a measure of firms' distance to the reassigned technology as an inverse measure of technological propinquity, following Akcigit et al. (2016). I obtain data from 1990 to 2006 from the National Bureau of Economic Research (NBER) Patent Citation database (Hall et al., 2001). I extend the patent and citation data using the Harvard Business School (HBS) patent database, including information on citations received by each patent until 2010. Following Hall et al. (2001) and Atanassov (2013), I also scale the raw number of citations of a patent by the average number of citations in the same technology class in the same year.[16]

2.4.2 Variables

This section describes the main variables used to analyze the relationship between common ownership and patent reassignments. A full list of variables and definitions can be found in Table 2.1.

Main independent variable: Common Ownership

I construct several measures of common ownership on the firm-pair level.

Profit weights. A natural candidate for a firm-pair measure of common ownership is the empirical counterpart of the profit weight λ the assignor puts on the profits of the potential assignee, as in my theoretical model (see section 2.3.1). Since I cannot observe the Pareto weights a manager puts on each investor, I follow the literature and assume

[15] Some large institutional investors such as BlackRock report their holdings further disaggregated at the asset manager level. I take this into account and aggregate this information when necessary, following Gilje et al. (2020)

[16] I give more details on this in section 2.4.2, where I describe the construction of the variables that proxy for the technological propinquity of firms.

proportional control. Therefore, my first measure of common ownership incentives of firm A with respect to firm B is calculated as follows:

$$\kappa_{all,AB} \equiv \frac{\sum_i \beta_{iA}\beta_{iB}}{\sum_i \beta_{iA}^2}, \tag{2.12}$$

where $i = 1, 2, 3...$ indexes the investors and β_{ij} is the share of stocks hold by investor i in company $j \in \{A, B\}$.

To relax the assumption of proportional control, I also calculate variations of this measure where I restrict the set of investors to those that at least hold 1%, 2%, or 5% in the technology provider. The reason is that tiny investors may not have the power to influence managerial decisions effectively. Furthermore, not restricting for the size of holdings could lead to overestimating the influence of common owners that hold very small shares of the assignor since the sum of squares of these holdings appears in the denominator of the measure. Therefore, I construct the variables $\kappa_{1\%,AB}$, $\kappa_{2\%,AB}$, and $\kappa_{5\%,AB}$.

GGL measures. Investors, including the common owners, may differ in how they monitor the managerial decisions of firms in their portfolios. Therefore, I also use the class of measures provided by Gilje et al. (2020) that take into account the portfolio weights of investors to proxy the attention an investor allocates to a firm. Their measures are computed in the following way:

$$GGL_{AB} = \sum_i \beta_{iA} g(\rho_{iA}) \beta_{iB}, \tag{2.13}$$

where i indexes investors, A, B are two different firms, and β_{iA} and β_{iB} are the share of equity hold by investor i in firm A and B, respectively. The weight of firm A in investor i's portfolio is ρ_{iA}, i.e., the ratio of the value of the investment of investor i in firm A to investor i's assets under management. Thus, the function $g(\cdot)$ proxies for the probability that an investor pays attention to firm A's management's decisions. Intuitively, the incentives of a manager to internalize the common ownership interests of an investor i increases with the shares of this investor in the firm (β_{iA}). It also increases with the ownership share of the investor in the other firm (β_{iB}), since this influences how much manager A's decisions affect investor i's portfolio value through its effect on firm B's profits. Finally, the measure increases in the probability $g(\rho_{iA})$ that the investor pays attention to the manager's decisions.

A crucial feature of the GGL class of measures is that it is flexible to accomodate different assumptions on the functional form of $g(\cdot)$, i.e., how investor attention depends on the portfolio weight of the firm. Gilje et al. (2020) compute their measures for different assumptions on $g(\cdot)$. They propose, in particular, versions with *full attention* ($g(\rho_{iA}) = 1$), *linear* ($g(\rho_{iA}) = \rho_{iA}$), *concave* ($g(\rho_{iA}) = \rho_{iA}^{1/2}$) , and *convex* ($g(\rho_{iA}) = \rho_{iA}^2$) specifications for $g(\cdot)$.

Table 2.1: 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
Independent variables	
Measures of common ownership:	
$\kappa_{all,AB}$	Profit weight as defined in 2.4.2 that takes into account all institutional investors in the assignor and their cross-holdings in the assignee
$\kappa_{x\%,AB}$	Profit weight that takes into account the cross-holdings of investors that hold at least x% of the assignor's outstanding shares
$GGL_{\text{Linear},AB}$	GGL measure (Gilje et al., 2020) that assumes that investor attention is a linear funtion of the firms' portfolio weight in the investor's portfolio
$GGL_{\text{FullAttention},AB}$	GGL measure that assumes full attention of investors
$GGL_{\text{Concave},AB}$	GGL measure that assumes a concave attention function
$GGL_{\text{Convex},AB}$	GGL measure that assumes a convex attention function
$GGL_{\text{Fitted},AB}$	GGL measure using a attenfunction fitted to actual voting behavior as describe in section 2.4.2
Technological distance measures:	
$d_{mean_{B,r}}$	Distance measure equally weighting the distances between firm B and each patent in reassignment r
$d_{weighted_{B,r}}$	Distance measure weighting the distances between firm B and each patent in reassignment r by citations
$d_{most\_cited_{B,r}}$	Distance of firm B to the most cited patent in reassignment r
$d_{most\_recent_{B,r}}$	Distance of firm B to the most recent patent in reassignment r
Control variables	
InstOwn	Percentage of firm's outstanding shares held by 13F institutions (Thomson Reuters s34 file)
Pstock	Average number of patents per year that a firm applied for since 1975 and that were finally granted.
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× cash flow [(♯18 + ♯14)/♯8] plus 0.283× Tobin's Q plus 3.139× Leverage minus 39.368× dividends [(♯21 + ♯19)/♯8] minus 1.315× cash holdings (♯1/♯8), where ♯8 is lagged
GovIndex	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
Instruments	
S&P500	Indicator variable equal to one if both firms in the firm pair observation belong to the S&P500 index constituents and zero otherwise
Russell1000	Indicator variable equal to one if both firms in the firm pair observation belong to the Russell1000 index constituents and zero otherwise
Russelltop200	Indicator variable equal to one if both firms in the firm pair observation belong to the Russelltop200 index constituents and zero otherwise

Furthermore, motivated by the evidence from Iliev and Lowry (2015), Gilje et al. (2020) also fit $g(\rho_{iA})$ to the likelihood that an investor is attentive using an indicator for whether an institution's votes fail to follow the recommendations of the proxy advisor *International Shareholder Services (ISS)*. Proxy advisory firms are often accused of giving "blanket recommendations" or following a one-size-fits-all approach.[17] Suppose investors increase their attention to a given firm in their portfolios. In that case, they are more likely to gather information and form an independent opinion about the corporate proposals they have to vote on. Thus, they are less likely to follow those "blanket recommendations" of a proxy advisor. The fitted attention function exhibits a concave relationship between portfolio weights and investor attention and is used by Gilje et al. (2020) to construct another version of their measure, GGL_{Fitted}.[18] Gilje et al. (2020) scale the measures by its sample average so that a value of one indicates the average level of incentives. Since this increases the variance of the measures and leads to very small coefficients in the probit regressions, I rescale the variables by dividing them by one thousand.

Technological Distance

To control for the technological proximity of the reassigned technology to a potential assignee, I construct technological distance measures between the bundle of patents that is sold and the patent stock of the potential buyers. First, I follow Akcigit et al. (2016) to construct a distance metric on the technology space and a measure of technological distance between an individual patent and a firm. Then, I aggregate the distances of each individual patent for the bundle that is reassigned. I use different methods to aggregate these distances for all patents in the bundle.

The distance between two 2-digit IPC technology classes X and Y is given by

$$d(X,Y) = 1 - \frac{||(X \cap Y)||}{||(X \cup Y)||}, \tag{2.14}$$

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 technology classes. I use all patents from 1975 to 2006 to construct this measure. With this metric on the technology classes I proceed by constructing the distances of individual patents to a firm's patent portfolio at a given year. The patent portfolio of a firm contains all patents it applied for since 1975 and that were finally granted. Then, the

[17]See Iliev and Lowry (2015) as a reference on ISS recommendations. See also Coles et al. (2008) and Johnson et al. (2015) for illustrative evidence that one-size-fits-all approaches may not be optimal with regard to Board size and takeover defenses, respectively.

[18]See Gilje et al. (2020) for details on how this measure is constructed. I thank the authors for providing the data.

distance between a patent and a firm is given by

$$d_\iota(f,p) = \left[\frac{1}{||\mathcal{P}_f||} \sum_{p' \in \mathcal{P}_f} d(X_p, Y_{p'})^\iota \right]^{\frac{1}{\iota}}, \tag{2.15}$$

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

As mentioned above, I aggregate this measure for all patents $p \in \mathcal{R}$. The bundle $\mathcal{R}$ is the set of patents in reassignment r. For robustness, I perform the aggregation in different ways.

The baseline version of my technological measures weights the patents in the reassignment r by citations, i.e.,

$$d_{weighted_{f,r}} = \sum_{p \in \mathcal{R}} d_\iota(p,f) w_p, \tag{2.16}$$

where w_p is the weight of each patent, i.e., the number of citations the patent received 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 the patents in the reassignment, such that $\sum_{p \in \mathcal{R}} w_p = 1$.

The second measure is very similar. I average the distance measures $d_\iota(f,p)$ for each patent in the reassignment without weighting by citations. The unweighted mean distance between the patent bundle and a firm's patent stock is given by

$$d_{mean_{f,r}} = \frac{1}{||\mathcal{R}||} \sum_{p \in \mathcal{R}} d_\iota(p,f). \tag{2.17}$$

The third measure of technological distance only takes into account the distance to the most cited patent in the reassignment, i.e.,

$$d_{\text{most\_cited}_{f,r}} = d_\iota(p(w_p^{max}), f), \tag{2.18}$$

where $p(w_p^{max})$ is the identity of the patent with the maximum weight w_p in the reassignment.

Finally, I construct a measure that takes into account the age of the patents. Citations measure the impact a patent has for later innovation and the patent value. However, for a given reassignment, the most recent innovation may be more important for its profitability. Let a_p be the age of a patent p and a_p^{min} the minimum age of the patents in the reassignment. Then, the last measure of technological distance is given by

$$d_{\text{most\_recent}_{f,r}} = d_\iota(p(a_p^{min}), f). \tag{2.19}$$

Dependent Variable

This paper analyzes how common ownership influences the probability that two firms engage in technology transfer. Therefore, the dependent variable is a binary outcome variable. I construct the dummy variable $Reass_{AB,r}$ that takes the value one if firm A reassigns technology r to firm B in a given year and zero otherwise.

Control Variables

As usual in the financial economics literature on innovation, I control for several firm characteristics. First, I construct the measure *InstOwn* to control for total institutional ownership (i.e., the share of stocks held by all 13F institutions in a firm). Second, I compute a measure of a firm's patent stock, *Pstock*. That is the natural logarithm of one plus the average number of all patents per year a firm has applied for since 1975 and which were finally granted.

The other control variables are *FirmSize*, which is the natural logarithm of total assets; *R&DtoAssets*, which corresponds to R&D expenses scaled by total assets; *FirmAge*, which is the number of years a firm has existed in Compustat; *Leverage*, which is the ratio of firm debt to total assets; *CashtoAssets*, which corresponds to firms' cash scaled by total assets; *Profitability*, which is the return on equity (ROE), and *Tobin's Q* gauging firm's growth potential; *PPE*, which is computed as firms' property, plant, and equipment (PPE) scaled by total assets; *CapextoAssets*, which corresponds to firms' capital expenditures scaled by total assets; *MarketCap*, which measures firm's market capitalization at the fiscal year end; and the *KZindex* which is a measure of financial constraints (Kaplan and Zingales, 1997). Another variable that has been shown to influence corporate innovation is the number of financial analysts that issue forecasts for a firm. Therefore, I control for the natural logarithm of one plus the number of financial analysts, *AnalystCoverage*.[19] I also include an index of corporate governance, *CGIndex*, following a similar approach to the one in Bertrand and Mullainathan (2001). To mitigate the effect of outliers, I winsorize *Profitability* and the *KZIndex* at the 1st and 99th percentiles. Table 2.1 contains a complete list and definitions of the variables.

2.5 Sample construction and descriptive statistics

I construct a data set on the firm-pair-technology level. An observation in the data set is a firm pair that may trade a particular technology, i.e., a bundle of patents that actually was reassigned in a particular year during the sample period 1990-2006.

First, I collect all firm pairs consisting of the assignor and the actual assignee that trade a bundle of patents in a given year. Then, similarly to Bena and Li (2014), in their paper on

[19]See Guo et al. (2019) for detailed information on how this variable is constructed. I thank the authors for providing the data.

acquisitions, I add potential counterfactual pairs to these observed traders in the technology market. The counterfactual pairs consist of the same assignor and counterfactual assignees. Each pair is constructed using the actual assignor since only the actual technology provider can transfer the concrete bundle of patents. This allows to control for the trade of the specific bundle of patents and its distance to the patent stock of a potential assignee, rather than for a more noisy measure of technological overlap between firms. To gauge the influence of the technological distance, I assume that the counterfactual pairs trade the same technology. Therefore the technological distance of the counterfactual assignees is the one to the patent bundle that is traded by the actual seller-buyer pair. All pairs in the sample are restricted to firms that have at least been granted one patent since 1975 in order to gauge their technological propinquity. To control for their differences in innovation intensity I control for the Patent Stock (*Pstock*) and the innovation expenses (*R&D*) of all potential assignees.

The counterfactual assignees are taken from the same 2-digit sic industry as the actual assignee. I select firms in the same 2-digit sic industry since the reassigned technology may serve in some sectors of the economy but not in others. This first sample where I consider all the possible counterfactual pairs contains 129,319 firm-pair observations, among which 146 pairs of firms actually trade patents.

Second, I construct two other samples in which I select a subset of the counterfactial observations as in Bena and Li (2014). In particular, I perform a propensity score matching on technological distance, patent stock, R&D intensity, firm size, firm age, and Tobin's Q. As I will show in section 2.7.1, these variables have the most explanatory power for the selection of the assignee in the full sample (besides common ownership). Therefore, I use these measures to select suitable counterfactual assignees. Since propensity score matching may increase imbalances of the sample by pruning observations (King and Nielsen, 2019), I also construct a Mahalanobis distance matched sample using the same assignee characteristics to test robustness. In each of these matched samples I select up to 10 counterfactual assignees that are close to the actual assignee in terms of the propensity score or the Mahalanobis distance, respectively.

Table 2.2 presents summary statistics for the 146 actual technology adopters (assignees) in the technology market between 1990 and 2006. In table 2.3, I report the main characteristics of the technology providers. These are not used in the regression analysis since they do not vary between factual and counterfactual pairs for each deal group.

Table 2.4 presents a comparison of summary statistics for the actual counterfactual assignees in different samples. All common ownership measures but $\kappa_{all,AB}$ are larger for the actual assignees than for the counterfactual firms in the Full Sample. Similarly, the technological distances are smaller for the actual assignees than for entire set of control firms, i.e., the actual assignees are technologically closer to the reassigned bundle of patents compared to the control group. Furthermore, the actual assignees have more institutional ownership, for which I control in all regressions. Also actual assignees have a larger patent stock, higher R&D intensity, are larger, older and have more growth potential.

Table 2.2: **Summary Statistics of actual Assignees.** This table reports the descriptive statistics for the variables of my regressions based on the full sample of actual traders in the market for technology from 1990 to 2006.

Variable	25th percentile	Median	Mean	75th percentile	Std. Dev.	No. of Obs.
Dependent variable						
$Reass_{AB,r}$	1.000	1.000	1.000	1.000	0.000	146
Independent variables						
$\kappa_{all,AB}$	0.330	0.641	0.795	0.996	0.712	146
$\kappa_{1\%,AB}$	0.280	0.517	0.666	0.891	0.563	146
$\kappa_{2\%,AB}$	0.184	0.410	0.618	0.881	0.646	146
$\kappa_{5\%,AB}$	0.000	0.019	0.199	0.240	0.333	146
$GGL_{\text{Linear},AB}$	1.265	9.115	31.938	42.041	55.976	139
$GGL_{\text{FullAttention},AB}$	28.569	50.199	65.192	89.957	60.517	139
$GGL_{\text{Concave},AB}$	56.289	196.909	335.470	499.457	381.553	139
$GGL_{\text{Convex},AB}$	0.002	0.036	0.657	0.371	1.737	139
$GGL_{\text{Fitted},AB}$	59.132	195.192	256.714	398.653	254.062	139
$d_{mean_{B,r}}$	0.335	0.598	0.557	0.775	0.285	146
$d_{weighted_{B,r}}$	0.329	0.600	0.556	0.783	0.291	146
$d_{most\_cited_{B,r}}$	0.237	0.577	0.539	0.834	0.318	146
$d_{most\_recent_{B,r}}$	0.242	0.577	0.539	0.791	0.317	146
Controls						
$InstOwn_B$	0.506	0.645	0.630	0.789	0.213	146
$Pstock_B$	2.048	3.202	3.282	4.249	1.594	146
$R\&DtoAssets_B$	0.030	0.072	0.111	0.141	0.139	146
$FirmSize_B$	6.532	7.947	7.932	9.401	2.135	146
$FirmAge_B$	2.079	3.068	2.856	3.850	1.028	146
$Tobin'sQ_B$	1.421	2.598	4.260	5.322	4.913	146
$KZindex_B$	-4.400	-0.950	-4.094	0.386	12.010	146
$Profitability_B$	0.116	0.300	0.250	0.460	0.524	146
$PPEtoAssets_B$	0.122	0.195	0.244	0.333	0.165	146
$CapextoAssets_B$	0.024	0.042	0.057	0.078	0.051	146
$CashtoAssets_B$	0.034	0.111	0.205	0.294	0.216	146
$AnalystCoverage_B$	2.048	2.624	2.511	3.016	0.714	146
$Leverage_B$	0.042	0.194	0.205	0.310	0.170	146
$GovIndex_B$	-0.295	0.014	0.036	0.334	0.495	146
HHI_B	0.112	0.178	0.334	0.480	0.276	146
HHI^2_B	0.012	0.032	0.187	0.230	0.272	146
Instruments						
S&P500	0.000	0.000	0.363	1.000	0.483	146
Russell1000	0.000	0.000	0.452	1.000	0.499	146
Russelltop200	0.000	0.000	0.158	0.000	0.366	146

Table 2.4 shows also the same summary statistics for the matched samples. As can be seen from the control variables, the matched control firms are more similar to the actual assignees in terms of *Pstock*, *R&DtoAssets*, *FirmSize*, *FirmAge*, and *Tobin'sQ* compared to the full sample. They are, on average, also closer to the reassigned technology than in the

Table 2.3: **Summary Statistics of technology provider characteristics.** This table reports descriptive statistics for main characteristics of the technology providers from 1990 to 2006.

Variable	25th percentile	Median	Mean	75th percentile	Std. Dev.	No. of Obs.
$InstOwn_A$	0.484	0.610	0.596	0.733	0.207	143
$Pstock_A$	2.050	3.931	3.495	4.742	1.771	143
$R\&DtoAssets_A$	0.025	0.058	0.079	0111	0.076	140
$FirmSize_A$	6.687	8.517	8.336	10.190	2.492	142
$FirmAge_A$	2.639	3.676	3.295	3.932	0.792	142
$Tobin'sQ_A$	1.350	1.694	3.105	2.781	4.337	138

Table 2.4: **Comparison of actual and counterfactual Assignees in different Samples.** This table reports summary statistics for main characteristics of the Assignees for the different samples.

	Assignees		Control groups					
Sample:	Full Sampel		Full Sampel		Propensity Score		Mahalanobis	
Variable	Median	Mean	Median	Mean	Median	Mean	Median	Mean
Dependent variable								
$Reass_{AB,r}$	1.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Independent variables								
$\kappa_{all,AB}$	0.641	0.795	0.484	1.516	0.452	0.689	0.494	0.683
$\kappa_{1\%,AB}$	0.517	0.666	0.367	0.502	0.375	0.498	0.413	0.540
$\kappa_{2\%,AB}$	0.410	0.618	0.281	0.406	0.311	0.445	0.330	0.472
$\kappa_{5\%,AB}$	0.019	0.199	0.000	0.122	0.012	0.154	0.015	0.160
$GGL_{\text{Linear},AB}$	9.115	31.938	2.606	15.462	4.821	21.956	5.226	24.293
$GGL_{\text{FullAttention},AB}$	50.199	65.192	26.218	37.859	41.266	51.707	42.029	52.284
$GGL_{\text{Concave},AB}$	196.909	335.470	74.349	174.127	127.016	247.438	129.291	260.565
$GGL_{\text{Convex},AB}$	0.036	0.657	0.005	0.341	0.015	0.407	0.017	0.526
$GGL_{\text{Fitted},AB}$	195.192	256.714	77.117	140.739	131.563	195.642	137.382	202.748
$d_{mean_{B,r}}$	0.598	0.557	0.961	0.823	0.653	0.617	0.702	0.647
$d_{weighted_{B,r}}$	0.600	0.556	0.967	0.827	0.647	0.615	0.704	0.644
$d_{most\_cited_{B,r}}$	0.577	0.539	0.984	0.829	0.682	0.609	0.722	0.636
$d_{most\_recent_{B,r}}$	0.577	0.539	0.980	0.817	0.694	0.615	0.748	0.647
Controls								
$InstOwn_B$	0.645	0.630	0.532	0.510	0.611	0.586	0.631	0.599
$Pstock_B$	3.202	3.282	1.204	1.532	3.363	3.328	2.853	2.913
$R\&DtoAssets_B$	0.072	0.111	0.060	0.101	0.079	0.112	0.057	0.088
$FirmSize_B$	7.947	7.932	5.753	5.940	7.977	7.986	7.712	7.588
$FirmAge_B$	3.068	2.856	2.639	2.687	2.890	2.903	3.091	2.952
$Tobin'sQ_B$	2.598	4.260	2.020	3.192	2.338	4.436	2.198	3.204

entire set of control firms. The average common ownership level in terms of all the different measures is smaller for the matched sample control pairs than for the actual trading pairs. Since there are still differences on average between the actual and counterfactual pairs in the matched samples, I include the control variable on which I have matched the controls in the respective regressions.

2.6 Econometric Analysis

I am interested in which pairs of firms engage in technology transfer. I estimate the coefficients of the independent variables in a sample of cross-sections of actual firm pairs that engage in technology transfer and control pairs constructed from actual assignors and counterfactual assignees. As in Banal-Estañol et al. (2018) and Arqué-Castells and Spulber (2021), I estimate the following counterfactual-probit model:

$$Reass_{AB,rtj} = \beta_0 + \beta_1 CO_{AB,tj} + \beta_2 d_{B,rtj} + \delta X_{B,tj} + \eta_t + \nu_j + u_{AB,rtj}, \tag{2.20}$$

where A indicates the actual seller of a technology (the assignor), B indicates the potential buyers (assignees), and r indicates the reassignment, i.e., the bundle of patents reassigned by firm A to some firm B in year t. The subscript j indicates firm B's 3-digit sic industry. The dependent variable of the binary outcome model $Reass_{AB,rtj}$ takes the value one if firm A sells technology r to firm B in year t. $CO_{AB,tj}$ is one of the common ownership measures; the technological distance between the potential assignees and the reassigned technology is captured by the variable $d_{B,rtj}$; $X_{B,tj}$ is a vector of firm characteristics; and η_t and ν_j are year and industry fixed effects, respectively. Since the counterfactual assignees are in the same 2-digit sic industry, I use 3-digit sic industry fixed effects to capture any unobserved differences in the propensity of technology adoption between these industries.

Furthermore, I estimate a similar model by running conditional logit regressions, as in Bena and Li (2014).[20] Since I model the technology transfer decision as a choice of the assignor to select a suitable assignee in the theoretical part of the paper, the conditional logit may fit better to capture this choice of the assignor. I estimate the following equation:

$$Reass_{AB,rtj} = \beta_0 + \beta_1 CO_{AB,tj} + \beta_2 d_{B,rtj} + \delta X_{B,tj} + \zeta_r + u_{AB,rtj}, \tag{2.21}$$

where ζ_r is the reassignment or group fixed effect.

As described in section 2.5, I construct matched samples, where I exclude observations with counterfactual assignees that are too different from the actual assignee. Then, after estimating (2.20) and (2.21) for the whole sample, I estimate (2.20) and (2.21) in the matched samples with counterfactual-probit and conditional logit, respectively.

The matching of counterfactual pairs similar to the actual traders in the technology market provides a more balanced sample and helps control for the assignee firms' unobservable characteristics. However, the estimation of the effect of common ownership on

[20] For an introduction to the conditional logit model, see McFadden (1974). Besides Bena and Li (2014) in their paper on acquisitions, conditional logit regressions were used in other applications in Finance. See, for example, Kuhnen (2009) and Dyck et al. (2010).

reassignments can still be biased due to reverse causality. For example, it may not be very plausible that large institutional investors decide to invest in two firms (or increase their holdings) because of a patent trade. However, institutional investors could invest more frequently in innovative firms, and these firms could have a higher propensity to trade patents. Therefore, I control for the innovativeness of firms using the average patents granted per year (*Pstock*) and the research intensity *R&DtoAssets*. Nevertheless, I will further address the issue of reverse causality by instrumenting the common ownership measures and estimating an instrumental variable (IV) model in section 2.7.4.

For the IV, I estimate equation (2.20) instrumenting the common ownership measures with three excluded instruments. The instruments are dummy variables that take the value one if both firms of the pair are constituents of the same stock market index and zero otherwise. In particular, I use firms' membership in the *S&P500*, the *Russelltop200* and the *Russell1000* indices. Institutional investors often offer investment instruments that benchmark against these indices. These index-tracking institutions invest in the indices' constituents, which leads to higher common ownership among these firms (Newham et al., 2019; Gilje et al., 2020). Hence, the instruments satisfy the relevance condition. Since the index-trackers invest in these firms only because of their membership in the index, the effect on common ownership is unrelated to the firms' innovativeness or engagement in technology transfer. Thus, the instruments do not affect patent trades but through the impact on common ownership and can be considered exogenous.

I will estimate the IV model running a probit regression using maximum-likelihood estimation and by a linear probability model using the usual two-stage least squares estimator. For this estimator, I use the following first stage regression:

$$\begin{aligned} CO_{AB,tj} = \alpha_0 + \alpha_1 \mathit{S\&P500}_{AB,tj} + \alpha_2 \mathit{Russelltop200}_{AB,tj} + \alpha_3 \mathit{Russell1000}_{AB,tj} \\ + \alpha_4 d_{B,rtj} + \alpha_5 X_{B,tj} + \eta_t + \nu_j + \varepsilon_{AB,rtj}, \end{aligned} \tag{2.22}$$

where $\mathit{S\&P500}_{AB,tj}$, $\mathit{Russelltop200}_{AB,tj}$, and $\mathit{Russell1000}_{AB,tj}$ are the three excluded instruments, and $X_{B,tj}$ are the control variables.[21] In all regressions presented in this paper, I report robust standard errors clustered at the reassignment-group level.

2.7 Empirical Results

In this section, I present my empirical results. I first estimate equations (2.20) and (2.21) for the entire sample, i.e., the sample of firm pairs consisting of actual assignors and actual and counterfactual assignees of a given technology. The counterfactual assignees are all Compustat firms, as described above, that are in the same 2-digit SIC industry

[21] The inclusion in an index depends on the market capitalization of firms. Since the value of the respective instrument depends on the inclusion of both firms in the index, I control in the IV regressions for the market capitalisation of the assignee $MarketCap_B$, the ratio of market capitalization of the two firms $MarketCapRatio_{AB} = MarketCap_B / MarketCap_A$, and the square of this ratio, $MarketCapRatio^2_{AB}$.

as the actual assignee of the technology and have been granted at least one patent since 1975. Then, I estimate the same relationship in my matched samples as described in sections 2.5 and 2.6. After that, I investigate the relationship between common ownership and reassignments, taking into account the complexity of the technology to test if moral hazard in technology transfer plays a crucial role in explaining the impact of common ownership. Finally, I provide the results of the IV estimation to establish causality.

2.7.1 Common Ownership and Reassignments

Table 2.5 presents the regression results for the full sample using the variables that are based on the empirical counterpart of the profit weights as measures of common ownership. In column (1), $\kappa_{all\%,AB}$ is used to gauge the strength of common ownership incentives of the assignor with respect to the potential assignees. The coefficient is negative and not significant. If common ownership incentives play a role for the selection of the assignee, as stated in Hypothesis 1, then this measure does not capture well the strength of these incentives. A plausible reason for this is that in many firms, common owners hold relatively small shares in the assignor. However, these investors may not have sufficient power to induce managers to act in their interest. Therefore, I use the measures in which I restrict the set of investors to those that at least hold 1%, 2%, or 5%, respectively, of the assignor's outstanding shares. Columns (2)-(3) present the results using $\kappa_{1\%,AB}$, $\kappa_{2\%,AB}$, and $\kappa_{5\%,AB}$ as measures of common ownership incentives. All three coefficients are positive and highly significant. These measures seem to capture the influence of common owners that hold a sufficiently large stake in the assignor on the probability of engaging in technology transfer with a given assignee. The results support Hypothesis 1.

Furthermore, the results in Table 2.5 also support Hypothesis 2. The technological distance between the potential assignees' patent stock and the reassigned technology is negative and significant at the 1% level in all four regressions. I have chosen to include my preferred measure of technological distance, $d_{weighted_{B,r}}$. In the next section, I will test the robustness of the result, using the other measures described in section 2.4.2.

Some of the coefficients of the other control variables are also significant and have the expected sign. For example, more innovative firms may have a higher absorptive capacity and profit more from adopting technologies developed outside the firm. For this reason, the coefficients of the potential buyers' long-term innovativeness, measured by *Pstock*, and their innovation intensity, *R&DtoAssets*, are positive and significant. Furthermore, firms are also more likely to adopt technologies if they are younger, larger, and have higher growth potential as seen from the coefficients of *FirmAge*, *FirmSize*, and *Tobin'sQ*, respectively.

In Table 2.6, I present the results when I use the different versions of the GGL class of measures, instead of the profit weights, to account for common ownership. All versions but one show a significant positive coefficient. Interestingly, the one coefficient that is not significant in the regression is GGL_{Convex} in column (4) that assumes that investor attention is a convex function of the firm's weight in the investor's portfolio. As I mentioned

Table 2.5: **Probit, Common Ownership and Reassignments (Profit weights, full sample).** This table reports coefficient estimates from probit models in equation (2.20) using the whole sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
$\kappa_{all,AB}$	-0.002			
	(0.003)			
$\kappa_{1\%,AB}$		0.141***		
		(0.030)		
$\kappa_{2\%,AB}$			0.170***	
			(0.037)	
$\kappa_{5\%,AB}$				0.157**
				(0.072)
$InstOwn_B$	0.347**	0.259	0.239	0.312*
	(0.158)	(0.163)	(0.166)	(0.161)
$d_{weighted_{B,r}}$	-1.250***	-1.258***	-1.257***	-1.251***
	(0.109)	(0.111)	(0.111)	(0.109)
$Pstock_B$	0.151***	0.152***	0.152***	0.152***
	(0.035)	(0.035)	(0.035)	(0.035)
$R\&DtoAssets_B$	1.153***	1.153***	1.143***	1.155***
	(0.177)	(0.178)	(0.177)	(0.176)
$FirmSize_B$	0.134***	0.137***	0.136***	0.135***
	(0.039)	(0.040)	(0.040)	(0.040)
$FirmAge_B$	-0.283***	-0.286***	-0.288***	-0.282***
	(0.051)	(0.051)	(0.051)	(0.051)
$Tobin'sQ_B$	0.023***	0.024***	0.023***	0.023***
	(0.006)	(0.006)	(0.006)	(0.006)
$KZindex_B$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$Profitability_B$	-0.086	-0.085	-0.085	-0.082
	(0.064)	(0.063)	(0.063)	(0.061)
$PPEtoAssets_B$	0.457	0.445	0.443	0.461
	(0.328)	(0.327)	(0.329)	(0.328)
$CapextoAssets_B$	-0.174	-0.145	-0.132	-0.179
	(0.921)	(0.918)	(0.924)	(0.920)
$CashtoAssets_B$	-0.379*	-0.386*	-0.385*	-0.379*
	(0.229)	(0.230)	(0.230)	(0.229)
$AnalystCoverage_B$	0.074	0.078	0.078	0.072
	(0.055)	(0.056)	(0.056)	(0.055)
$Leverage_B$	0.174	0.177	0.170	0.169
	(0.163)	(0.165)	(0.165)	(0.163)
$GovIndex_B$	0.030	0.026	0.026	0.031
	(0.062)	(0.062)	(0.062)	(0.062)
HHI_B	0.476	0.446	0.454	0.473
	(0.686)	(0.693)	(0.695)	(0.685)
HHI_B^2	-0.346	-0.327	-0.330	-0.343
	(0.657)	(0.664)	(0.665)	(0.657)
Industry-FE	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES
Observations	129319	129319	129319	129319
Pseudo-R^2	0.229	0.232	0.233	0.230

Table 2.6: **Probit, Common Ownership and Reassignments (GGL, Full sample).** This table reports coefficient estimates from probit models in equation (2.20) using the whole sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			$Reass_{AB,r}$		
$GGL_{\text{Linear},AB}$	0.679***				
	(0.236)				
$GGL_{\text{FullAttention},AB}$		2.260***			
		(0.531)			
$GGL_{\text{Concave},AB}$			0.219***		
			(0.052)		
$GGL_{\text{Convex},AB}$				1.633	
				(1.662)	
$GGL_{\text{Fitted},AB}$					0.445***
					(0.102)
$InstOwn_B$	0.316*	0.191	0.258	0.339**	0.217
	(0.167)	(0.177)	(0.169)	(0.167)	(0.174)
$d_{weighted_{B,r}}$	-1.262***	-1.264***	-1.267***	-1.261***	-1.268***
	(0.113)	(0.114)	(0.114)	(0.113)	(0.113)
$Pstock_B$	0.148***	0.145***	0.147***	0.148***	0.146***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
$R\&DtoAssets_B$	1.207***	1.209***	1.204***	1.212***	1.209***
	(0.169)	(0.168)	(0.169)	(0.169)	(0.168)
$FirmSize_B$	0.131***	0.128***	0.128***	0.133***	0.128***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
$FirmAge_B$	-0.277***	-0.274***	-0.276***	-0.277***	-0.275***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
$Tobin'sQ_B$	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$KZindex_B$	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Profitability_B$	-0.035	-0.037	-0.035	-0.035	-0.037
	(0.047)	(0.046)	(0.047)	(0.047)	(0.047)
$PPEtoAssets_B$	0.500	0.481	0.493	0.498	0.476
	(0.334)	(0.337)	(0.335)	(0.334)	(0.336)
$CapextoAssets_B$	-0.142	-0.112	-0.138	-0.146	-0.123
	(0.925)	(0.923)	(0.925)	(0.926)	(0.926)
$CashtoAssets_B$	-0.332	-0.338	-0.335	-0.329	-0.339
	(0.232)	(0.229)	(0.232)	(0.231)	(0.230)
$AnalystCoverage_B$	0.075	0.073	0.076	0.074	0.074
	(0.057)	(0.057)	(0.057)	(0.056)	(0.057)
$Leverage_B$	0.187	0.184	0.183	0.187	0.179
	(0.173)	(0.173)	(0.174)	(0.173)	(0.174)
$GovIndex_B$	0.028	0.024	0.028	0.029	0.026
	(0.062)	(0.063)	(0.062)	(0.062)	(0.062)
HHI_B	0.574	0.512	0.554	0.573	0.527
	(0.690)	(0.688)	(0.692)	(0.689)	(0.689)
HHI_B^2	-0.468	-0.400	-0.448	-0.467	-0.420
	(0.671)	(0.673)	(0.674)	(0.669)	(0.672)
Industry-FE	YES	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES	YES
Observations	118847	118847	118847	118847	118847
Pseudo-R^2	0.229	0.233	0.231	0.228	0.232

Table 2.7: **Cond. Logit, Common Ownership and Reassignments (Full sample).** This table reports coefficient estimates from conditional logit models in equation (2.21) using the whole sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include reassignment-group fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
$\kappa_{1\%,AB}$	0.129***			
	(0.022)			
$\kappa_{5\%,AB}$		0.675***		
		(0.248)		
$GGL_{\text{FullAttention},AB}$			10.042***	
			(1.632)	
$GGL_{\text{Fitted},AB}$				1.947***
				(0.316)
$InstOwn_B$	1.756***	1.681***	1.121**	1.266***
	(0.423)	(0.438)	(0.462)	(0.452)
$d_{weighted_{B,r}}$	-4.142***	-4.102***	-4.001***	-4.007***
	(0.338)	(0.337)	(0.347)	(0.346)
$Pstock_B$	0.493***	0.496***	0.497***	0.497***
	(0.080)	(0.080)	(0.083)	(0.083)
$R\&DtoAssets_B$	3.113***	3.076***	3.166***	3.144***
	(0.494)	(0.490)	(0.471)	(0.475)
Controls	YES	YES	YES	YES
Reassignment-FE	YES	YES	YES	YES
Observations	147378	147378	118847	118847
Pseudo-R^2	0.221	0.221	0.233	0.232

in section 2.4.2, when Gilje et al. (2020) fit the attention function to actual voting data, the relationship between investor attention and portfolio weights exhibits a concave functional form. Thus, a concave attention function seems to be a more realistic model of how common ownership interests translate into managerial incentives and decision-making. The convex measure seems to be less sensible in the studied context, and I will exclude it from the following analysis. The coefficients of the other GGL measures support Hypothesis 1. Common ownership incentives influence the match of an assignee to a technology provider.

In most of the analysis that follows, I will present a subset of the results for brevity. Therefore, I choose two measures of each class as my preferred measures of common ownership incentives. For the profit weights, a natural choice is to use $\kappa_{1\%,AB}$. As a second measure for this class, I will also report results for $\kappa_{5\%,AB}$ since a holding of 5% corresponds to the traditional definition of blockholders in financial economics literature.[22] Regarding the GGL class, we see from Table 2.6 that the two measure that fit best the data in terms of the *Pseudo-*R^2 are $GGL_{\text{FullAttention},AB}$ and $GGL_{\text{Fitted},AB}$. Therefore, I will use these as my preferred measures.

Next, I will use my preferred measures to estimate (2.21) running a conditional logit regression. This model of choice may better capture the selection of the assignee by the assignor. Table 2.7 shows the results. They are consistent with those obtained through the previous probit regressions. The coefficients of the four measures of common ownership are all positive and significant at the 1% level supporting Hypothesis 1. The coefficient of the

[22] See, for example, He and Huang (2017).

technological distance measure is significantly negative at the 1% level in all regressions, which supports my Hypothesis 2.

Matched Sample Analysis

In Tables 2.5 and 2.6, we have seen the influence not only of common ownership but also of the other covariates on the probability that a reassignment takes place for a given firm pair. I use these variables that significantly explain technology transfer except common ownership to construct the matched samples. I select up to ten counterfactual pairs for each actual trading pair. The matched counterfactuals are the closest in technological distance, patent stock, R&D intensity, firm size, firm age, and Tobin's Q to the actual assignees in terms of their propensity score or the Mahalanobis distance, respectively. The assignor firm in the counterfactual pairs is the same as in the real pair. Furthermore, counterfactual assignees are exactly matched concerning the year and the 2-digit sic industry of the actual assignee.

I present the results for the propensity score and Mahalanobis distance matched samples in Table 2.8. Panel A shows the regression coefficients of the preferred measures for common ownership in the probit regression using the propensity score matching. The coefficients are all positive and significant supporting the results in Tables 2.5 and 2.6. The size of the coefficients is larger than in the full sample regressions.

Panel B presents the results of the conditional logit model. Also in this specification, the coefficients confirm the results in the initial analysis qualitatively and support Hypothesis 1. Panels C and D estimate the counterfactual-probit and the conditional logit models, respectively, using the Mahalanobis distance matched sample. Some of the coefficients are less significant. However, the qualitative results are confirmed, showing a positive impact of the common ownership measures.

2.7.2 Technological distance and Reassignments

In this section, I confirm the impact of common ownership and technological distance using the different technological distance measures I described in section 2.4.2. $d_{B,r}$ is the technological distance between the potential assignee firm and the reassigned technology, i.e., the bundle of patents transferred. The different distance measures vary in the way in which they aggregate the technological distance measure à la Akcigit et al. (2016) between the individual patents in the bundle and the potential buyers' patent stock.

Table 2.9 presents the results for the different measures of technological distance, including $\kappa_{1\%,AB}$ as a measure of common ownership and using the full sample.[23] Panel A shows the results estimating the counterfactual-probit model, and in Panel B, conditional logit regressions are presented. In all specifications, the corresponding measure of technological distance has the expected negative sign and is significant at the 1% level. Thus, the

[23] Results are qualitatively similar if I use the other measures of common ownership.

Table 2.8: **Common Ownership and Reassignments (Matched Samples).** This table reports key coefficient estimates for the different common ownership measures from probit (Panels A and C) and conditional logit models (Panels B and D) in equations (2.20) and (2.21), respectively, using the propesity score (Panels A and B) and Mahalanobis distance matched samples (Panels C and D) of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one for the firm pairs AB that engage in the transfer of the reassignment r and zero for the control pairs that form the control group. All specifications include either industry and year or reassignment-group fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Probit, propensity score matching				
	(1)	(2)	(3)	(4)
Dependent variable:			$Reass_{AB,r}$	
Measure of CO_{AB}:	$\kappa_{1\%,AB}$	$\kappa_{5\%,AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	0.451***	0.351**	3.265**	0.795***
	(0.102)	(0.169)	(1.280)	(0.237)
$InstOwn_B$	-0.110	0.188	0.026	0.021
	(0.339)	(0.304)	(0.326)	(0.324)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	1101	1101	1101	1101
Pseudo-R^2	0.166	0.154	0.157	0.161
Panel B: Conditional logit, propensity score matching				
	(1)	(2)	(3)	(4)
Dependent variable:			$Reass_{AB,r}$	
Measure of CO_{AB}:	$\kappa_{1\%,AB}$	$\kappa_{5\%,AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	1.049***	0.660*	10.673***	2.284***
	(0.273)	(0.356)	(2.720)	(0.542)
$InstOwn_B$	0.506	1.087**	0.588	0.662
	(0.541)	(0.468)	(0.500)	(0.482)
Controls	YES	YES	YES	YES
Reassignment-FE	YES	YES	YES	YES
Observations	1443	1443	1443	1443
Pseudo-R^2	0.088	0.066	0.085	0.086
Panel C: Probit, Mahalanobis distance matching				
	(1)	(2)	(3)	(4)
Dependent variable:			$Reass_{AB,r}$	
Measure of CO_{AB}:	$\kappa_{1\%,AB}$	$\kappa_{5\%,AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	0.193*	0.318*	2.827**	0.677***
	(0.101)	(0.164)	(1.161)	(0.212)
$InstOwn_B$	0.131	0.214	0.079	0.082
	(0.310)	(0.298)	(0.309)	(0.307)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	1062	1062	1062	1062
Pseudo-R^2	0.194	0.193	0.196	0.197
Panel D: Conditional logit, Mahalanobis distance matching				
	(1)	(2)	(3)	(4)
Dependent variable:			$Reass_{AB,r}$	
Measure of CO_{AB}:	$\kappa_{1\%,AB}$	$\kappa_{5\%,AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	0.726***	0.594	8.089***	1.851***
	(0.235)	(0.423)	(2.591)	(0.657)
$InstOwn_B$	0.940*	1.295**	0.866	0.909
	(0.561)	(0.561)	(0.578)	(0.567)
Controls	YES	YES	YES	YES
Reassignment-FE	YES	YES	YES	YES
Observations	1397	1397	1397	1397
Pseudo-R^2	0.198	0.190	0.202	0.201

Table 2.9: **Technological Distance (different measures, full sample).** This table reports key coefficient estimates for the different measures of technological distance and common ownership from probit (Panels A) and conditional logit models (Panels B) in equations (2.20) and (2.21), respectively, using the whole sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one for the firm pairs AB that engage in the transfer of the reassignment r and zero otherwise. All specifications include either industry and year or reassignment-group fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Probit				
	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
CO_{AB}	0.142***	0.141***	0.137***	0.137***
	(0.030)	(0.030)	(0.029)	(0.029)
$InstOwn_B$	0.257	0.259	0.258	0.251
	(0.163)	(0.163)	(0.162)	(0.161)
$d_{mean_{B,r}}$	-1.278***			
	(0.115)			
$d_{weighted_{B,r}}$		-1.258***		
		(0.111)		
$d_{most\_cited_{B,r}}$			-1.106***	
			(0.096)	
$d_{most\_recent_{B,r}}$				-1.066***
				(0.098)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	129319	129319	129319	129319
Pseudo-R^2	0.233	0.232	0.228	0.225
Panel B: Conditional Logit				
	(5)	(6)	(7)	(8)
Dependent variable:		$Reass_{AB,r}$		
CO_{AB}	0.130***	0.129***	0.125***	0.125***
	(0.022)	(0.022)	(0.022)	(0.023)
$InstOwn_B$	1.749***	1.756***	1.753***	1.721***
	(0.422)	(0.423)	(0.425)	(0.423)
$d_{mean_{B,r}}$	-4.181***			
	(0.352)			
$d_{weighted_{B,r}}$		-4.142***		
		(0.338)		
$d_{most\_cited_{B,r}}$			-3.546***	
			(0.280)	
$d_{most\_recent_{B,r}}$				-3.415***
				(0.271)
Controls	YES	YES	YES	YES
Reassignment-FE	YES	YES	YES	YES
Observations	147378	147378	147378	147378
Pseudo-R^2	0.220	0.221	0.216	0.211

results strongly support Hypothesis 2. Furthermore, they are in line with similar results by Akcigit et al. (2016) on the patent level.

The measures of technological distance performing best in the analysis are those that average the distances to all the individual patents in the bundle. These measures have the largest coefficients and perform best in terms of the *Pseudo*-R^2. Thus, I use the citation weighted distance measure $d_{weighted}$ as my preferred measure of technological distance.

2.7.3 Testing for Moral Hazard: The influence of technological complexity

In this section, I study the mechanism that explains a part of the impact of common ownership on patent reassignments and the selection of the assignee. We have seen in sections 2.7.1 and 2.7.2 that the effect of common ownership is positive and significant. In section 2.3.3, I have presented a theoretical model that can explain this effect. In the model, common ownership alleviates the moral hazard problem in transferring the unverifiable part of the technology: specialized know-how. The know-how transfer increases the deal's value and, therefore, helps the assignor increase its profits when selling to a firm with which it has more common ownership.

In section 2.3.3, I have argued that technologies may differ in the extent to which the transfer of specialized know-how is required for their adoption by the assignee. More complex technologies require specialized know-how stemming from different technological areas. These complex technologies are more likely to require a know-how transfer from the assignor to the assignee firm. Hence, the agency problem in transferring this know-how is more severe when complex technologies are traded. Therefore, the effect of common ownership should be stronger for these technologies (Hypothesis 3).

To capture the complexity of a reassigned technology, I construct a measure that uses the IPC classes of the patents in the bundle. A technology combines more knowledge from different technological areas and, thus, is more complex if the patents in the bundle are dispersed in different IPC classes. Let s_X be the share of patents in a reassigned bundle r that falls into the 2-digit IPC class X. Then, the complexity of the reassigned technology is given by:

$$Complexity_r = 1 - \sum_X s_X^2, \tag{2.23}$$

that is, the inverse of the concentration of patents in the IPC classes.

To test Hypothesis 3, I run the counterfactual-probit regression including $Complexity_r$ and its interaction with the common ownership measure. If Hypothesis 3 is supported, then the interaction term should be positive and significant, i.e., the higher the complexity of the technology, the stronger should the effect of common ownership be.

In the conditional logit regressions I cannot include the same interaction term as in the probit regressions. This is due to the group fixed effects that would capture the effect of the technologies' complexity since the complexity does not vary within groups. Therefore, I construct a dummy variable, $ComplexDummy_r$, that takes the value one if the reassigned technology is more complex than the median technology in the sample and zero otherwise. I include this interaction term of $ComplexDummy_r$ and the common ownership measure in the conditional-logit model.

Table 2.10 presents the results for the different specifications and common ownership measures. Panel A shows the results of the probit regressions for the profit weights using the full sample. Besides for $\kappa_{all,AB}$ (column 1) which does not capture well the common

Table 2.10: **Common Ownership and technological Complexity.** This table reports key coefficient estimates for the different common ownership measures and its interaction with a measure of technological complexity from probit (Panels A, B and C) and conditional logit models (Panel D), using the full sample (Panels A and C) and the propensity score matched sample (Panels B and D) of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable $Reass_{AB,r}$ is equal to one for the firm pairs AB that engage in the transfer of the reassignment r and zero otherwise. In Panels A, B, and C the respective measure of common ownership is interacted with a continuous measure of complexity. In Panel D it is interacted with a binary variable that takes the value one if the reassigned technology is more complex than the median technology in the sample. All specifications include either industry and year or reassignment-group fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Profit weights, full sample, Probit				
	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$\kappa_{all,AB}$	$\kappa_{1\%,AB}$	$\kappa_{2\%,AB}$	$\kappa_{5\%,AB}$
CO_{AB}	-0.011	0.096**	0.096	0.051
	(0.014)	(0.043)	(0.063)	(0.091)
$CO_{AB} \times Complexity_r$	0.016	0.183**	0.247*	0.492**
	(0.019)	(0.092)	(0.141)	(0.250)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	129319	129319	129319	129319
Pseudo-R^2	0.230	0.233	0.234	0.232
Panel B: Profit weights, propensity score matched sample, Probit				
	(5)	(6)	(7)	(8)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$\kappa_{all,AB}$	$\kappa_{1\%,AB}$	$\kappa_{2\%,AB}$	$\kappa_{5\%,AB}$
CO_{AB}	0.006	0.318***	0.175*	0.341*
	(0.038)	(0.119)	(0.104)	(0.206)
$CO_{AB} \times Complexity_r$	0.159	0.799**	0.786**	0.068
	(0.099)	(0.380)	(0.324)	(0.644)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	1101	1101	1101	1101
Pseudo-R^2	0.153	0.170	0.164	0.154
Panel C: GGL measures, full sample, Probit				
	(9)	(10)	(11)	(12)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$GGL_{\text{Linear},AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Concave},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	0.200	1.463**	0.152**	0.305**
	(0.539)	(0.718)	(0.071)	(0.129)
$CO_{AB} \times Complexity_r$	1.619	3.196*	0.272	0.743*
	(1.866)	(1.659)	(0.238)	(0.388)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	118847	118847	118847	118847
Pseudo-R^2	0.229	0.234	0.231	0.233
Panel D: propensity score matched sample, Cond. Logit				
	(13)	(14)	(15)	(16)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$\kappa_{1\%,AB}$	$\kappa_{5\%,AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	0.624*	-0.055	5.329	1.054
	(0.319)	(0.497)	(3.311)	(0.644)
$CO_{AB} \times ComplexDummy_r$	0.826	1.547**	12.846**	3.644**
	(0.576)	(0.784)	(6.033)	(1.524)
Controls	YES	YES	YES	YES
Reassignment-FE	YES	YES	YES	YES
Observations	1443	1443	1443	1443
Pseudo-R^2	0.093	0.071	0.094	0.100

ownership incentives, as seen in Table 2.5 of section 2.7.1, for all measures of this class in columns (2)-(4), the interaction term is positive and significant. Thus, the effect of these profit weights increases as the complexity of the technology increases. This fact lends support to Hypothesis 3. Also, in Panel B, we find evidence for the differential effects of common ownership for different degrees of complexity of the technology using the propensity score matched sample. The interaction term is positive in all four regressions and is significant at the 5% level for $\kappa_{1\%,AB}$ and $\kappa_{2\%,AB}$.

Panel C estimates the relationship using the GGL measures and the full sample. The interaction terms are all positive. They are significant at the 10% level in columns (2) and (4) for my preferred measures in this class.

Finally, Panel D shows results for my four preferred measures and the conditional logit regression using the propensity score matching and including the interaction with the $ComplexDummy_r$. For all measures of common ownership, the coefficients of the interaction term are positive. Moreover, they are significant at the 5% level for all but one measure. Notice also that the size of the coefficients of the interaction term in columns (2)-(4) are larger in size than the coefficient of the respective common ownership measures, which are not significant. This indicates that the positive effect of common ownership mainly comes from the reassignments of more complex technologies.

Summing up, the results in this section provide support for Hypothesis 3. Furthermore, they suggest that moral hazard plays a crucial role in transferring technologies and that giving incentives to the assignor to transfer specialized know-how can partly explain the positive impact of common ownership.

2.7.4 Robustness Check: Addressing reverse causality

In this section, I further address the concern that common ownership is endogenous. To do so, I instrument the common ownership variables using the strategy described in section 2.6. First, I use my propensity score matched sample to estimate a linear probability model by two-stage least squares (2SLS).[24] The first-stage equation is given by (2.22), and the second-stage equation is given by (2.20). Second, I estimate an IV probit model of (2.20) since the dependent variable is a binary outcome variable. To cluster standard errors at the reassignment level, I use maximum likelihood estimation.

Table 2.11 presents the results of the linear probability model for the profit weights. The odd columns report the first-stage regressions. Each following even column presents the corresponding second-stage regression. Column (1) presents the first-stage regression to instrument $\kappa_{all,AB}$. The coefficient of the *S&P500* instrument shows the expected positive sign and is highly significant. The coefficients of the other instruments are smaller and less significant. The Kleibergen-Paap F-statistic reported at the bottom of column (2) indicates that the regression does not suffer from weak identification. The p-value of the Hansen J statistic shows that we cannot reject the null hypothesis that the instruments are valid.

The coefficient of $\kappa_{all,AB}$ in the second stage regression in column (2) is positive and significant. The same holds for the following two measures of common ownership, $\kappa_{1\%,AB}$ and $\kappa_{2\%,AB}$ in columns (4) and (6). The coefficient of $\kappa_{5\%,AB}$ is also positive although not significant. As the Kleibergen-Paap F-statistic indicates, the instruments do not explain well the common ownership for the larger blockholders in the assignor. Indeed, none of

[24] The results for the full sample (untabulated) are qualitatively very similar.

Table 2.11: **Linear Probability model, IV 2SLS, propensity score matched sample, profit weights.** This table reports key coefficient estimates from IV linear probability models in equations (2.20) and (2.22) using the instrumental variable strategy described in section 2.6 for the propensity score sample of actual and counterfactual firm pairs of technology providers and potential adopters. Odd columns report the first stage regression. Each following even column reports the corresponding second-stage regression. The dependent variable in the second stage is $Reass_{AB,r}$ and is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Profit weights								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	$\kappa_{all,AB}$	$Reass_{AB}$	$\kappa_{1\%,AB}$	$Reass_{AB}$	$\kappa_{2\%,AB}$	$Reass_{AB}$	$\kappa_{5\%,AB}$	$Reass_{AB}$
$\kappa_{all,AB}$		0.113***						
(instrumented)		(0.039)						
$\kappa_{1\%,AB}$				0.126***				
(instrumented)				(0.040)				
$\kappa_{2\%,AB}$						0.142***		
(instrumented)						(0.040)		
$\kappa_{5\%,AB}$								0.233
(instrumented)								(0.460)
$InstOwn_B$	0.438*	0.002	0.640***	-0.029	0.551***	-0.028	0.155***	0.016
	(0.254)	(0.057)	(0.075)	(0.047)	(0.073)	(0.045)	(0.043)	(0.083)
S&P500	0.370***		0.331***		0.265***		0.042	
	(0.066)		(0.050)		(0.052)		(0.031)	
RUSSELtop200	0.099*		0.098*		0.078		-0.053*	
	(0.052)		(0.051)		(0.060)		(0.031)	
RUSSEL1000	0.035		0.024		0.126**		0.004	
	(0.063)		(0.057)		(0.060)		(0.029)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1397	1397	1397	1397	1397	1397	1397	1397
Kleibergen-Paap F-statistic		13.997		22.999		17.948		1.222
p-value (Hansen J)		0.246		0.227		0.644		0.006

Table 2.12: **Linear Probability model, IV 2SLS, propensity score matched sample.** This table reports key coefficient estimates from IV linear probability models in equations (2.20) and (2.22) using the instrumental variable strategy described in section 2.6 for the propensity score sample of actual and counterfactual firm pairs of technology providers and potential adopters. Odd columns report the first stage regression. Each following even column reports the corresponding second-stage regression. The dependent variable in the second stage is $Reass_{AB,r}$ and is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	$GGL_{\text{Linear},AB}$	$Reass_{AB}$	$GGL_{\text{FullAttention},AB}$	$Reass_{AB}$	$GGL_{\text{Concave},AB}$	$Reass_{AB}$	$GGL_{\text{Fitted},AB}$	$Reass_{AB}$
$GGL_{\text{Linear},AB}$		1.329***						
(instrumented)		(0.366)						
$GGL_{\text{FullAttention},AB}$				1.613**				
(instrumented)				(0.655)				
$GGL_{\text{Concave},AB}$						0.138***		
(instrumented)						(0.036)		
$GGL_{\text{Fitted},AB}$								0.201***
(instrumented)								(0.057)
$InstOwn_B$	0.033***	0.006	0.056***	-0.041	0.317***	0.005	0.221***	0.004
	(0.007)	(0.043)	(0.006)	(0.052)	(0.056)	(0.043)	(0.034)	(0.043)
S&P500	0.026***		0.019***		0.263***		0.178***	
	(0.006)		(0.004)		(0.040)		(0.023)	
RUSSELtop200	0.006		-0.015***		-0.006		-0.051**	
	(0.007)		(0.004)		(0.040)		(0.021)	
RUSSEL1000	0.018***		0.013***		0.167***		0.116***	
	(0.006)		(0.005)		(0.037)		(0.019)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1397	1397	1397	1397	1397	1397	1397	1397
Kleibergen-Paap F-statistic		16.830		10.573		43.675		51.811
p-value (Hansen J)		0.763		0.151		0.575		0.398

Table 2.13: **IV Probit (full sample).** This table reports key coefficient estimates from IV probit models in equation (2.20) using maximum likelihood estimation and the instrumental variable strategy described in section 2.6 for the whole sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable is $Reass_{AB,r}$ and is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Profit weights				
	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$\kappa_{all,AB}$	$\kappa_{1\%,AB}$	$\kappa_{2\%,AB}$	$\kappa_{5\%,AB}$
CO_{AB}	0.063***	0.514***	0.562***	2.758***
(instrumented)	(0.021)	(0.193)	(0.198)	(0.721)
$InstOwn_B$	0.100**	0.047	0.046	-0.299
	(0.039)	(0.194)	(0.184)	(0.210)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	123298	123298	123298	123298
p-Wald	0.000	0.054	0.049	0.017
Panel B: GGL Measures				
	(5)	(6)	(7)	(8)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$GGL_{\text{Linear},AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Concave},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	4.015**	4.687	0..449**	0.673*
(instrumented)	(1.744)	(3.854)	(0.204)	(0.350)
$InstOwn_B$	0.268	0.098	0.237	0.210
	(0.171)	(0.255)	(0.173)	(0.177)
Controls	YES	YES	YES	YES
Industry and year FE	YES	YES	YES	YES
Observations	114788	114788	114788	114788
p-Wald	0.047	0.524	0.209	0.499

the coefficients of the instruments has a significantly positive effect. Nevertheless, the IV results for the profit weights in total are qualitatively similar to the results in section 2.7.1 and support Hypothesis 1.

Table 2.12 shows the corresponding results for the GGL measures. All four instrumented variables show positive and significant effects. Furthermore, the F-statistics are large, and the p-values of the Hansen J statistics are not significant. Therefore, I conclude that the linear probability IV results support Hypothesis 1. Common ownership has a positive effect on the probability that the firm pair engages in technology transfer.

Since I am using a binary outcome variable, I re-estimate the IV model using the maximum likelihood estimator for the probit regression (IV probit). The results are shown in Table 2.13 for the full sample and in Table 2.14 for the propensity score matching. Almost all the coefficients of the different common ownership measures are positive and significant in the two Tables. Only the coefficients of $GGL_{\text{FullAttention},AB}$ in column (6) of Table 2.13 and of $\kappa_{5\%,AB}$ in column (4) Table 2.14 are not significant, but they are still positive. As we have seen above, the latter may be caused by weak identification. However, the p-value of the Wald test of exogeneity indicates that a simple probit model is preferred in these two cases.

In general, the results of the IV estimation lend support for a positive effect of common ownership on technology transfer. They confirm Hypothesis 1.

Table 2.14: **IV Probit (Propensity score matched sample).** This table reports key coefficient estimates from IV probit models in equation (2.20) using maximum likelihood estimation and the instrumental variable strategy described in section 2.6 for the propensity score sample of actual and counterfactual firm pairs of technology providers and potential adopters. The dependent variable in the second stage is $Reass_{AB,r}$ and is equal to one if the firm pair AB engages in the transfer of the reassignment r and zero otherwise. All specifications include 3-digit sic industry and year fixed effects. Robust standard errors (clustered at the reassignment level) are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Profit weights				
	(1)	(2)	(3)	(4)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$\kappa_{all,AB}$	$\kappa_{1\%,AB}$	$\kappa_{2\%,AB}$	$\kappa_{5\%,AB}$
CO_{AB}	0.712***	0.890***	0.920***	3.280
(instrumented)	(0.218)	(0.276)	(0.249)	(2.421)
$InstOwn_B$	0.014	-0.263	-0.183	-0.247
	(0.409)	(0.368)	(0.335)	(0.671)
Industry and year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	1079	1079	1079	1079
p-Wald	0.005	0.145	0.026	0.525
Panel B: GGL Measures				
	(5)	(6)	(7)	(8)
Dependent variable:		$Reass_{AB,r}$		
Measure of CO_{AB}:	$GGL_{\text{Linear},AB}$	$GGL_{\text{FullAttention},AB}$	$GGL_{\text{Concave},AB}$	$GGL_{\text{Fitted},AB}$
CO_{AB}	9.425***	10.704***	0.990***	1.419***
(instrumented)	(2.402)	(3.553)	(0.251)	(0.388)
$InstOwn_B$	-0.002	-0.327	-0.012	-0.009
	(0.324)	(0.364)	(0.326)	(0.324)
Industry and year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	1079	1079	1079	1079
p-Wald	0.009	0.046	0.084	0.128

2.8 Conclusion

In this paper, I studied the impact of common ownership on patent reassignments. Specifically, I have analyzed how common ownership by institutional investors shapes the selection of the assignee. I outlined a model explaining how moral hazard can lead to a positive effect of common ownership on the propensity to transfer the technology to a particular firm. The model also describes the impact of the technological proximity of a potential buyer to the reassigned technology. Moreover, it motivates the investigation of the relationship between common ownership and assignee selection for technologies that differ in their complexity.

I test the hypotheses using USPTO reassignment data. To mitigate concerns about omitted variable bias, I have controlled for the R&D intensity and the patent stock of the potential assignees and employed different matching techniques to select counterfactual firm pairs that are most similar to the actual firm pair that engages in the reassignment of patents. In addition, I have used pairwise index membership of firms in the *S&P500*, *Russelltop200*, and *Russell1000* stock market indexes to address the issue of reverse causality. The effect of common ownership appears to be robust in these tests.

The empirical results confirm the predictions of my theoretical model. Common ownership increases the probability that a firm pair engages in technology transfer, and this effect is stronger if the reassigned technology is more complex. This fact suggests that moral hazard in know-how transfer is a plausible mechanism through which common ownership influences technology transfer, i.e., common ownership increases the incentives to transfer uncodified know-how.

As the theoretical mechanism in my model also applies to other modes of technology transfer, a prolific extension of my analysis is the study of the effect of common ownership on the matching of firms engaging in licensing, cross-licensing, and strategic alliances that include R&D cooperation. Furthermore, the positive effect of common ownership on the reallocation of technology and the dissemination of know-how must be weighed against its potential adverse consequences, such as the anti-competitive effects discussed in the literature. I leave these questions for future research.

Chapter 3

Automation and Sectoral Reallocation

3.1 Introduction

As a result of improved capabilities and falling production costs, the global operational stock of industrial robots rose by about 65% within five years (2013-2018). The Covid-19 pandemic crisis is expected to accelerate further the speed of automation (see, e.g., Dolado et al., 2020 and Leduc and Liu, 2020a). In addition to the potentially significant implications for labor markets, recent evidence reveals that higher exposure to robot adoption has increased support for nationalist and radical-right parties in Western Europe (Anelli et al., 2020).

Academic and policy debates have focused on whether robots cause job displacement or job creation in the economy. On the one hand, a negative displacement effect arises from the fact that robots can outperform workers in some tasks. For instance, Acemoglu and Restrepo (2020) find that each robot installed in the US replaces six workers. On the other hand, a positive productivity effect occurs because machines can help fewer workers produce more output, which increases labor demand. In this vein, the seminal work by Graetz and Michaels (2018) finds, using industry-level data from 17 countries, that cumulative changes in robot adoption from 1993 to 2007 boost labor productivity and raise wages.[1]

Notably, the adjustment in other parts of the economy – for instance, when other sectors expand to absorb the labor freed from robot adoption – has received little attention so far. According to empirical evidence for Germany in Dauth et al. (2021), industrial robots have changed the composition but not the aggregate size of employment, with job gains in services offsetting the negative impact on manufacturing employment. Figure 3.1

[1] There are two main strands in the literature regarding a tangible measure of automation: information-and-communication-technology capital (see, e.g., Eden and Gaggl, 2018) and robotics (see, e.g., Graetz and Michaels, 2018).

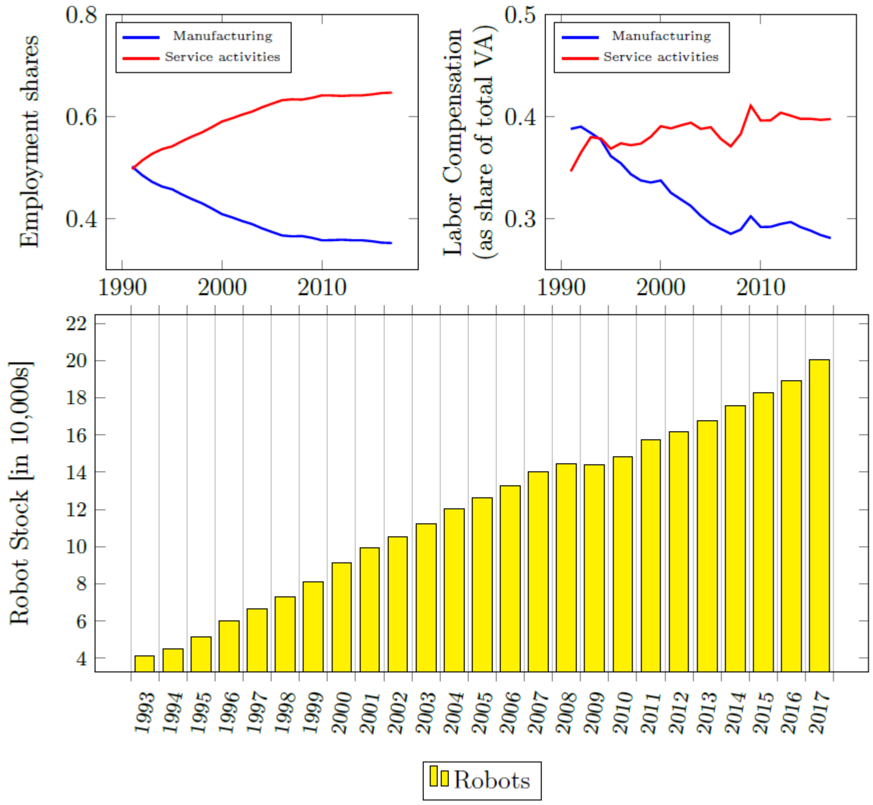

Figure 3.1: Robots, sectoral employment shares and labor compensation in Germany

Note: Employment shares and and labor compensation are calculated from EUKLEMS data. Data on the stock of industrial robots are from the International Federation of Robotics (IFR).

shows the evolution of the employment shares and labor compensation (as a share of value added (VA)) in the two sectors along with the stock of industrial robots. Germany is the country with the highest robot density in Europe (see Figure 3.2).[2]

To rationalize the empirical evidence on the automation-driven sectoral reallocation of labor in Germany, we develop a general equilibrium model with two production sectors, a labor market participation choice, and matching frictions.[3] Automation increases the capital intensity of the technology in the manufacturing sector as motivated by the microfoundations derived by Acemoglu and Restrepo (2018), consistently with empirical

[2]As one of the most important manufacturing exporters worldwide, Germany is a special case. Therefore, the results in this paper cannot be generalized to other economies without further research.

[3]For empirical work on the decline in manufacturing and the rise in services, see a novel dataset for 10 sectors, 23 countries, and 150 years compiled by Priftis and Shakhnov (2020).

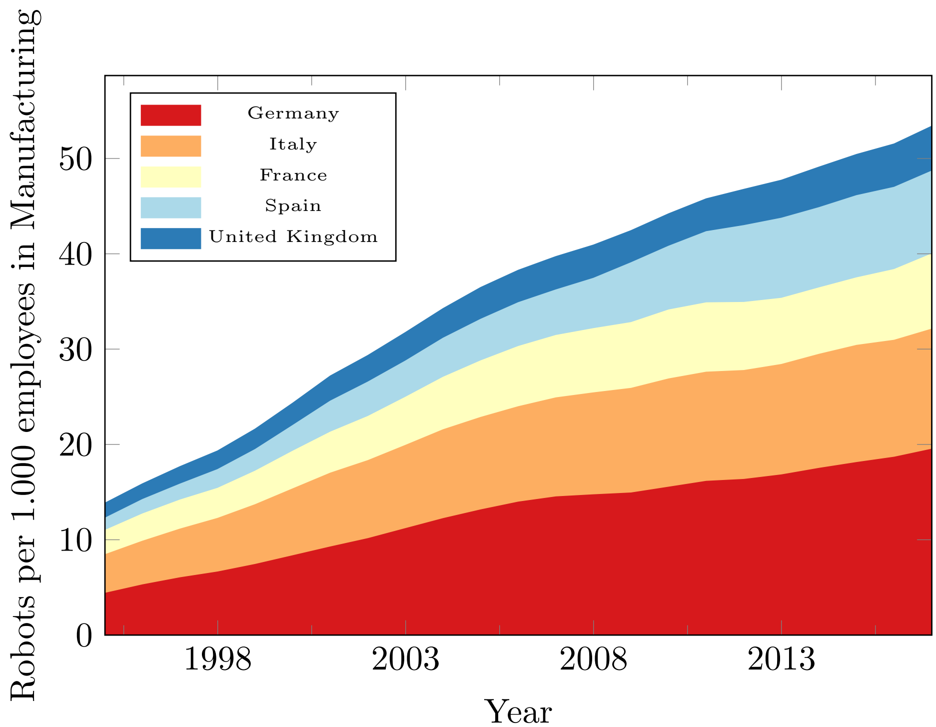

Figure 3.2: Industrial robot density in the manufacturing sector of European economies

Note: Data on the stock of industrial robots are from the International Federation of Robotics (IFR). We define the manufacturing sector as the aggregate of Industries A-F in the German WZ08 (NACE Rev. 2) industry classification.

observations, and close in spirit to Bergholt et al. (2021).[4] The presence of the extensive margin in our model is motivated by recent literature highlighting the negative effect of automation on participation, both in the short run and the long run (see, e.g., Grigoli et al., 2020; Lerch, 2020; and Jaimovich et al., 2020). Overall, the adjustment of sectoral labor markets in response to automation takes place in the model through three channels: (i) job creation, (ii) sector-specific search of unemployed job seekers, and (iii) participation. Since our representative household model is capable of rationalizing the empirical evidence mentioned above, we abstract from heterogeneous households for simplicity.

Calibrating the model for Germany and focusing on long-run analysis, we show that automation induces firms to create fewer vacancies and job seekers to search less in the robot-exposed sector (manufacturing). The model is able to replicate the empirical evo-

[4] Bergholt et al. (2021) examine impulse responses to an automation shock, modeled as an exogenous increase in the weight of capital in the production function of a New Keynesian model. They find that automation is the main driver of the long-run labor share.

lution of the sectoral employment shares and labor compensation in manufacturing and services (Figure 3.1). Labor demand in services increases due to two effects. Firstly, an increase in automation decreases the marginal cost in manufacturing in the long run. The two sectoral goods are gross complements in the production of the final consumption good. Therefore, the positive income effect on services dominates the negative substitution effect due to a decrease of the relative price of manufacturing caused by automation. This result is consistent with the model of Acemoglu and Restrepo (2020), where higher robot adoption increases demand for complementary inputs. Additionally, as more capital is accumulated in the steady state due to the exogenous increase in automation, the demand for the aggregate good increases (positive wealth effect). We show through analysis across steady states that the reduction in manufacturing employment can be offset by the increase in service employment, thus leaving aggregate employment unaffected, in line with the empirical findings of Dauth et al. (2021).

In the model, structural change due to automation leads to a reallocation of workers from the manufacturing sector to the service sector. Furthermore, the model generates a negative effect of automation on participation in line with the literature. As we seek to explain how total employment can consequently remain constant, the presence of unemployment is crucial to generate the patterns observed in the data. Without unemployment and endogenous participation, that would be true by construction.

Our analysis highlights vacancy creation (labor demand) as the primary channel through which the two labor markets adjust to automation. The elasticities of substitution between capital and labor in manufacturing production and between automatable (manufacturing) and non-automatable (service) goods play an important role in the sectoral reallocation of labor, while the sectoral mobility of job seekers and the strength of the positive income effect versus the negative substitution effect on the demand for services due to a change in relative prices also matter for the extent of sectoral reallocation.

Finally, the model can replicate the magnitude of the decline in the ratio of manufacturing employment to service employment in Germany from 1994 to 2014. Specifically, we take from the German data the values of the capital share in manufacturing in these two years. Then, we compute the values of the degree of automation in our model that generate these two values in the corresponding steady states, keeping the rest of the calibration unchanged. We find that in the second steady state (for 2014) the model predicts a decline of 34% in the ratio of manufacturing employment to service employment, which is close to the one found in the data (30%). In addition, the model predicts a fall in the aggregate labor share of 7.7%, which matches well the data value (7%).

Related Literature. The paper brings together the strands of the literature on automation and structural change. To the best of our knowledge, we are the first to build a two-sector general equilibrium model with labor market frictions to analyze the long-run impact of automation on both sectoral and aggregate employment. Very few studies in the automation literature have considered a multi-sector economy but without accounting for labor frictions. Focusing on inequality, Berg et al. (2018) show that the inclusion of a non-automation sector amplifies the high-skill labor gains and low-skill labor losses from automation. In an overlapping generations set up with also a non-automatable sector, Sachs et al. (2019) study the possibility of one generation improving their welfare at future generations' expense through robot adoption. The papers of Ngai and Pissarides (2008), Cruz and Raurich (2020) and Leon-Ledesma and Moro (2020) are examples of models that consider structural change with or without leisure (endogenous participation).[5] Our contribution to the structural change literature is to investigate the effects of automation as a driver of sectoral reallocation in a search and matching framework.

In macroeconomic models with labor frictions, the role of automation remains little explored. Leduc and Liu (2020b) provide the first quantitative general equilibrium evaluation of the interaction between automation and labor market fluctuations over the business cycle. Automation acts as an endogenous wage rigidity by posing a threat to workers in wage negotiations. Leduc and Liu (2020a) extend this model with nominal rigidities. They find that pandemic-induced uncertainty shocks to worker productivity stimulate automation, which helps mitigate the negative impact on aggregate demand.[6] We extend this literature by studying automation-driven sectoral reallocation.

Structure. Section 2 lays out the model. Section 3 establishes the equilibrium relationship between relative labor demand and labor supply in the two-sector economy. Section 4 discusses the parameterization. Section 5 presents the results. Section 6 investigates the role of key parameters and features of the model. Section 7 concludes.

3.2 The Model

We construct a general equilibrium model featuring search and matching frictions, endogenous labor decisions, and two sectors (manufacturing and services). Figure 3.3 provides an overview of the model.

On the production side, there is a representative firm in each of the two sectors. Manufacturing output is produced with capital and labor as inputs. Automation increases the capital intensity of the technology in the manufacturing sector. This can be motivated by the idea that some work operations, formerly performed by humans, are now executed by robots (Acemoglu and Restrepo, 2018). Output in services is also produced with labor and capital. The outputs of the two sectors are costlessly aggregated into the final consumption good.

On the household side, there is a representative household consisting of employees,

[5] See also the survey by Herrendorf et al. (2014) and the model of structural change, skills mismatch and matching frictions in Restrepo (2015).

[6] Models with automation, heterogeneous households, and matching frictions are developed by Cords and Prettner (2019) and Jaimovich et al. (2020) to study the impact on inequality.

unemployed job seekers, and labor force non-participants. The household rents out its capital to the manufacturing and service firms, purchases the final consumption good, and receives dividends through owning the two firms.

3.2.1 Labor markets

Jobs are created through a matching function. For $j = M, S$ denoting the manufacturing and service sectors, let υ_t^j be the number of vacancies and u_t^j the number of job seekers. We assume matching functions of the form,

$$m_t^j = \mu_1^j (\upsilon_t^j)^{\mu_2^j} (u_t^j)^{1-\mu_2^j}, \tag{3.1}$$

where the efficiency of the matching process is μ_1^j and μ_2^j denotes the elasticity of matches with respect to vacancies. For each sector, we define the hiring probability ψ_t^{hj} and the vacancy-filling probability ψ_t^{fj},

$$\psi_t^{hj} \equiv \frac{m_t^j}{u_t^j}, \qquad \psi_t^{fj} \equiv \frac{m_t^j}{\upsilon_t^j}.$$

Labor market tightness $\theta_t^j \equiv \upsilon_t^j / u_t^j$ determines the matching market prospects of firms and workers. The probability that a worker finds a vacancy is an increasing function of labor market tightness, $\psi_t^{hj} = f(\theta_t^j)$, while the probability that a job vacancy is matched with an unemployed worker is a decreasing function of tightness, $\psi_t^{fj} = f(\theta_t^j)/\theta_t^j$.

In each period, jobs are destroyed at a constant fraction σ^j and m_t^j new matches are formed. The law of motion of employment n_t^j is then given by,

$$n_{t+1}^j = (1-\sigma^j) n_t^j + m_t^j = (1-\sigma^j) n_t^j + \psi_t^{hj} u_t^j. \tag{3.2}$$

Using the vacancy-filling probability, we obtain an equivalent expression,

$$n_{t+1}^j = (1-\sigma^j) n_t^j + \psi_t^{fj} \upsilon_t^j. \tag{3.3}$$

3.2.2 Household

Next, we present the structure of the household side in the model and the corresponding optimization problem.

Utility function and budget constraint

The representative household consists of a continuum of infinitely lived members. Utility is derived from consumption c_t and from leisure, which corresponds to the fraction of members out of the labor force l_t. The instantaneous utility function is given by,

$$U(c_t, l_t) = \frac{c_t^{1-\eta}}{1-\eta} + \Phi \frac{l_t^{1-\varphi}}{1-\varphi},$$

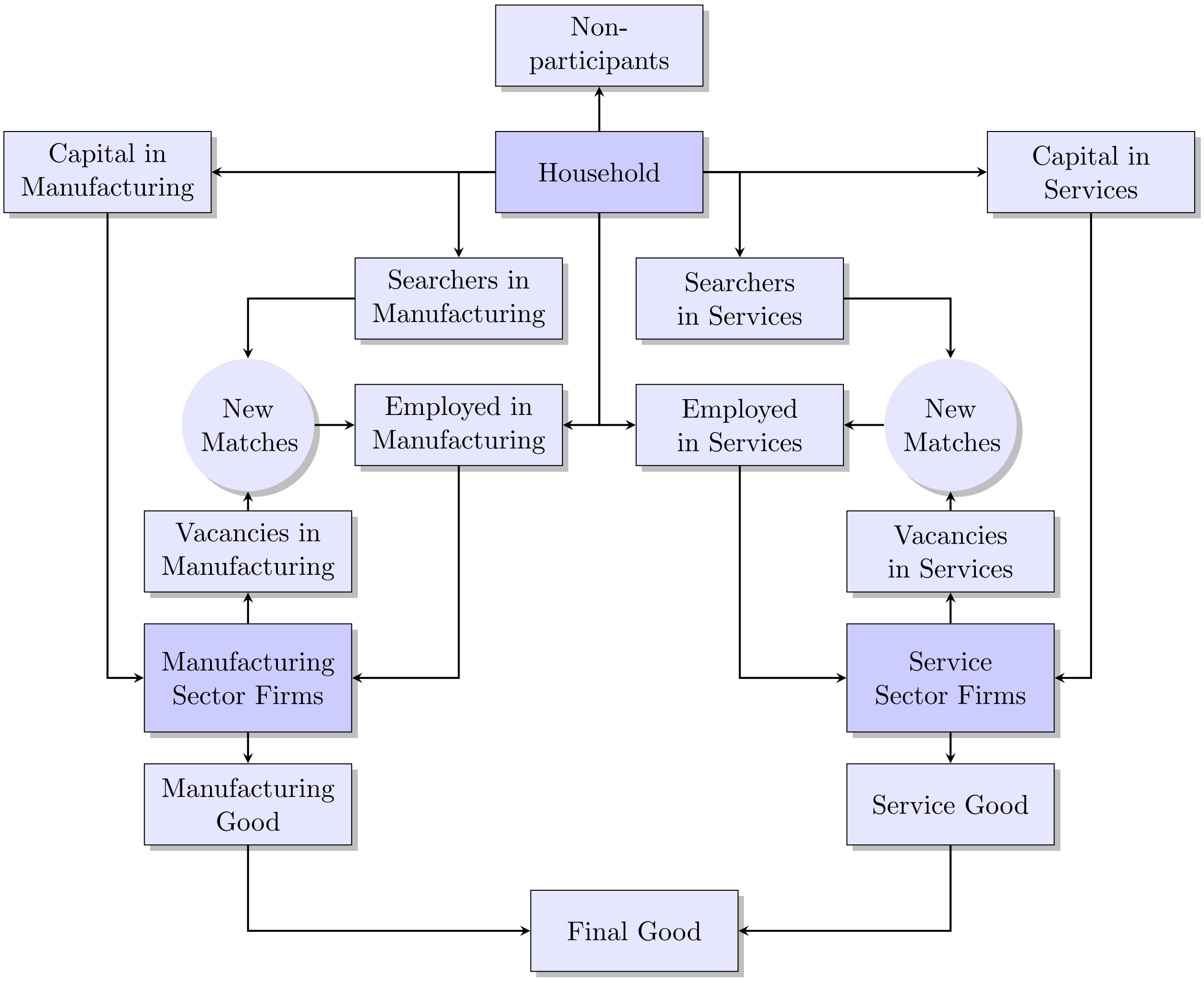

Figure 3.3: Model overview

where η is the inverse of the intertemporal elasticity of substitution, $\Phi > 0$ is the relative preference for leisure and φ is the inverse of the Frisch elasticity of labor supply. At any point in time, a fraction n_t^M (n_t^S) of the household's members are employees in the manufacturing (service) sector. The household chooses the fraction of the unemployed actively searching for a job u_t versus those who are out of the labor force enjoying leisure l_t so that

$$n_t^M + n_t^S + u_t + l_t = 1. \tag{3.4}$$

Of the unemployed u_t, the household chooses the fraction of job seekers who look for a job in the manufacturing sector s_t while the remaining $1 - s_t$ search in services, so that

$$u_t = s_t u_t + (1 - s_t)u_t = u_t^M + u_t^S, \tag{3.5}$$

where $u_t^M \equiv s_t u_t$ and $u_t^S \equiv (1 - s_t)u_t$. The household accumulates assets, evolving over time according to

$$k_{t+1} = i_t + (1 - \delta)k_t, \tag{3.6}$$

where i_t is investment and δ is a constant depreciation rate. The household budget constraint is given by,

$$c_t + i_t \leq r_t k_t + w_t^M n_t^M + w_t^S n_t^S + \bar{b}_t u_t - T_t + \Pi_t^M + \Pi_t^S, \tag{3.7}$$

where w_t^j is the real wage in each sector, r_t is the real return on assets, $\bar{b}_t$ is the unemployment benefit (see Section 3.4), T_t refers to lump-sum taxes that adjust to satisfy the government budget, i.e. $\bar{b}_t u_t = T_t$, and Π_t^j for $j = M, S$ denotes dividends received from ownership of the firms. We model the unemployment benefit as a share ϖ of the average wage in the economy through the function $\bar{b}_t = \varpi \frac{(w_t^M n_t^M + w_t^S n_t^S)}{n_t^M + n_t^S}$.

The optimization problem

The household maximizes the expected lifetime utility subject to equations (3.1), (3.2), (3.4), (3.5), (3.6), and (3.7) (for details, see Appendix B.2). Denoting by $\lambda_t^{n^M}$, $\lambda_t^{n^S}$, and λ_t^c the Lagrange multipliers on equations (3.2) for $j = S, M$ and (3.7), the first-order conditions with respect to c_t, k_{t+1}, n_{t+1}^M, n_{t+1}^S, u_t and s_t are given by,

$$c_t^{-\eta} = \lambda_t^c, \tag{3.8}$$

$$\lambda_t^c = \beta E_t \left[\lambda_{t+1}^c (1 - \delta + r_{t+1}) \right], \tag{3.9}$$

$$\lambda_t^{n^M} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^M + \lambda_{t+1}^{n^M} (1 - \sigma^M) \right], \tag{3.10}$$

$$\lambda_t^{n^S} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^S + \lambda_{t+1}^{n^S} (1 - \sigma^S) \right], \tag{3.11}$$

$$\Phi l_t^{-\varphi} - \lambda_t^{n^M} \psi_t^{hM} s_t - \lambda_t^{n^S} \psi_t^{hS}(1 - s_t) = \lambda_t^c \bar{b}_t, \tag{3.12}$$

$$\lambda_t^{n^M} \psi_t^{hM} = \lambda_t^{n^S} \psi_t^{hS}. \tag{3.13}$$

Equations (3.8) and (3.9) are the non-arbitrage conditions for the returns to consumption and capital. Equations (3.10) and (3.11) relate the expected marginal value of being employed in each sector to the utility loss from the reduction in leisure, the wage, and the continuation value, which depends on the separation probability. Equation (3.12) states that the value of being unemployed (rather than enjoying leisure) should equal the marginal utility from leisure minus the expected marginal values of being employed in each sector, weighted by the respective job finding probabilities and shares of job seekers. Equation (3.13) states the choice of the share s_t is such that the expected marginal values of being employed, weighted by the job finding probabilities, are equal in the two sectors. Notice that the marginal value to the household of an additional member employed in each sector is given by,

$$V^h_{n^{M_t}} = -\Phi l_t^{-\varphi} + \lambda_t^c w_t^M + (1 - \sigma^M)\lambda_t^{n^M}, \tag{3.14}$$

$$V^h_{n^{S_t}} = -\Phi l_t^{-\varphi} + \lambda_t^c w_t^S + (1 - \sigma^S)\lambda_t^{n^S}. \tag{3.15}$$

3.2.3 Production

We now turn to the structure of the production side in the economy and present the optimization problem of the firms in the two sectors.

Final good

There are three goods produced in the economy. These include two intermediate goods, namely manufacturing and service goods (M_t and S_t), which are combined in the production of the final good Y_t according to a CES technology,

$$Y_t = \left[\gamma M_t^{\frac{\chi-1}{\chi}} + (1-\gamma) S_t^{\frac{\chi-1}{\chi}}\right]^{\frac{\chi}{\chi-1}}, \tag{3.16}$$

where $0 < \gamma < 1$ denotes the weight attached to the manufacturing good versus the service good and χ is the elasticity of substitution.

The three goods are sold in competitive markets and we assume that the final good is the numeraire. Therefore, the prices of the sectoral goods equal the marginal products,

$$p_t^M = \frac{\partial Y_t}{\partial M_t} = \gamma \left(\frac{Y_t}{M_t}\right)^{\frac{1}{\chi}}, \tag{3.17}$$

$$p_t^S = \frac{\partial Y_t}{\partial S_t} = (1-\gamma)\left(\frac{Y_t}{S_t}\right)^{\frac{1}{\chi}}. \tag{3.18}$$

Manufacturing intermediate good

The manufacturing good is produced by combining capital k_t^M with employment n_t^M,

$$M_t = \left[\zeta (k_t^M)^{\frac{\alpha-1}{\alpha}} + (1-\zeta)(n_t^M)^{\frac{\alpha-1}{\alpha}}\right]^{\frac{\alpha}{\alpha-1}}, \tag{3.19}$$

where ζ denotes the weight attached to capital versus labor and α is the elasticity of substitution.

An increase in ζ makes output more capital-intensive at the expense of labor, representing in our setup an increased robot adoption (automation). The microeconomic foundations are derived by Acemoglu and Restrepo (2018) in a framework where a continuum of tasks is used in production. Automation in that context is interpreted as a shift in the share of tasks that can be produced with capital. Acemoglu and Restrepo (2018) show how one can aggregate the tasks to establish a production function with aggregate capital and labor inputs (see also the discussion in Bergholt et al., 2021).

Firms maximize the discounted expected value of future profits subject to the technology and the law of motion of employment (3.2). That is, they take the number of workers currently employed n_t^j as given and choose the number of vacancies to post υ_t^j so as to employ the desired number of workers next period n_{t+1}^j. The firm also chooses the amount of capital to demand. The manufacturing firm solves the problem,

$$Q^M(n_t^M) = \max_{\upsilon_t^M, k_t^M} \left\{ p_t^M M_t - w_t^M n_t^M - r_t k_t^M - \kappa^M \upsilon_t^M + E_t \left[\Lambda_{t,t+1} Q^M(n_{t+1}^M)\right] \right\}, \tag{3.20}$$

where κ^M denotes the marginal cost of posting a vacancy. As the household owns the firm, the term $\Lambda_{t,t+1} = \beta\lambda_{t+1}^c/\lambda_t^c$ refers to the household's stochastic discount factor in which λ_t^c denotes the Lagrange multiplier for the household budget constraint and β is the household's discount factor.

The first-order conditions with respect to υ_t^M and k_t^M are,

$$\kappa^M = \psi_t^{fM} \times E_t \Lambda_{t,t+1} \left[p_{t+1}^M (1-\zeta) \left(\frac{M_{t+1}}{n_{t+1}^M}\right)^{\frac{1}{\alpha}} - w_{t+1}^M + \frac{(1-\sigma^M)\,\kappa^M}{\psi_{t+1}^{fM}} \right], \tag{3.21}$$

$$r_t = p_t^M \cdot \zeta \left(\frac{M_t}{k_t^M}\right)^{\frac{1}{\alpha}}. \tag{3.22}$$

Equation (3.21) states that the marginal cost of hiring a worker should equal the expected marginal benefit subject to the vacancy-filling probability. The latter includes the net value of the marginal product of labor, where ζ enters with a negative sign, minus the wage plus the continuation value. Equation (3.22) states that the return on capital is equal to the value of its marginal product, where ζ enters with a positive sign.

The value of the marginal job for the firm is given by,

$$V^f_{n^M t} = p^M_t (1-\zeta) \left(\frac{M_t}{n^M_t} \right)^{\frac{1}{\alpha}} - w^M_t + \frac{\left(1-\sigma^M\right) \kappa^M}{\psi^{fM}_t}. \tag{3.23}$$

Service intermediate good

In the service sector, the production function is given by,

$$S_t = \left[\xi (k^S_t)^{\frac{\rho-1}{\rho}} + (1-\xi)(n^S_t)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{3.24}$$

where ξ denotes the weight attached to capital versus labor and ρ is the elasticity of substitution. A firm operating in this sector solves the following problem,

$$Q^S(n^S_t) = \max_{\upsilon^S_t, k^S_t} \left\{ p^S_t S_t - w^S_t n^S_t - r_t k^S_t - \kappa^S \upsilon^S_t + E_t \left[\Lambda_{t,t+1} Q^S(n^S_{t+1}) \right] \right\}, \tag{3.25}$$

The first-order conditions with respect to υ^S_t and k^S_t are,

$$\kappa^S = \psi^{fS}_t \times E_t \Lambda_{t,t+1} \left[p^S_{t+1} (1-\xi) \left(\frac{S_{t+1}}{n^S_{t+1}} \right)^{\frac{1}{\rho}} - w^S_{t+1} + \frac{\left(1-\sigma^S\right) \kappa^S}{\psi^{fS}_{t+1}} \right], \tag{3.26}$$

$$r_t = p^S_t \cdot \xi \left(\frac{S_t}{k^S_t} \right)^{\frac{1}{\rho}}. \tag{3.27}$$

The value to the firm of a marginal job is given by,

$$V^f_{n^S t} = p^S_t (1-\xi) \left(\frac{S_t}{n^S_t} \right)^{\frac{1}{\rho}} - w^S_t + \frac{\left(1-\sigma^S\right) \kappa^S}{\psi^{fS}_t}. \tag{3.28}$$

3.2.4 Wage bargaining

Following standard practice, the Nash bargaining problem in each sector is to maximize the weighted sum of log surpluses,

$$\max_{w^j_t} \left\{ \left(1-\vartheta^j\right) \ln V^h_{n^j t} + \vartheta^j \ln V^f_{n^j t} \right\}, \tag{3.29}$$

where ϑ^j denotes the bargaining power of firms and $V^h_{n^j t}$, $V^f_{n^j t}$ have been defined above. The first-order condition with respect to w^j_t is

$$\vartheta^j V^h_{n^j t} = \left(1-\vartheta^j\right)\lambda^c_t V^f_{n^j t}.$$

Through the derivations shown in the Appendix B.3, we obtain the equilibrium values for wages in the two sectors,

$$w^M_t = \left(1-\vartheta^M\right)\left(p^M_t(1-\zeta)\left(\frac{M_t}{n^M_t}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi^{fM}_t}\right) + \frac{\vartheta^M}{\lambda^c_t}(\Phi l_t^{-\varphi} - \left(1-\sigma^M\right)\lambda^{n^M}_t), \tag{3.30}$$

$$w^S_t = \left(1-\vartheta^S\right)\left(p^S_t(1-\xi)\left(\frac{S_t}{n^S_t}\right)^{\frac{1}{\rho}} + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi^{fS}_t}\right) + \frac{\vartheta^S}{\lambda^c_t}(\Phi l_t^{-\varphi} - \left(1-\sigma^S\right)\lambda^{n^S}_t). \tag{3.31}$$

3.2.5 Resource constraint

The final good is used for consumption and investment, and also to cover vacancy costs.

$$Y_t = c_t + i_t + \kappa^M \upsilon^M_t + \kappa^S \upsilon^S_t. \tag{3.32}$$

The derivation of the resource constraint is shown in Appendix B.4.

3.3 Relative Labor Demand and Supply in the Steady State

In this section, let us first provide the definition of steady-state equilibrium. We consider the long run as the interesting frequency given that the empirical counterpart of interest (Dauth et al. (2021)) focuses on long-run analysis, comparing the effects of automation in Germany between 1994 and 2014.

Steady-state equilibrium. *A steady-state equilibrium is a set of values for prices* $\{p^M, p^S, r, w^M, w^S\}$ *and endogenous variables,* $\{u, v^M, v^S, k^S, k^M, s\}$*, such that,*

1. *The law of motion of employment* (3.2) *holds in both sectors,*
2. *The prices of the intermediate sectoral goods,* p^M *and* p^S*, equal the goods' marginal products in the final good production, i.e.* (3.17) *and* (3.18) *are satisfied,*
3. *The problem of the representative household is solved (Section 3.2.2),*
4. *The problem of the representative firm in each sector (3.20 and 3.25) is solved,*

5. *Wages, w^M and w^S, solve the respective bargaining problems (3.29),*

6. *The capital market clears, i.e. $k = k^M + k^S$.*

Next, we establish the steady-state equilibrium relationship between relative labor demand and relative labor supply in the two sectors.

Proposition 1. *In the steady-state equilibrium, the sectoral ratio of labor market tightness depends only on the bargaining power and vacancy costs in the two sectors,*

$$\frac{\theta^M}{\theta^S} = \frac{\vartheta^M}{(1-\vartheta^M)} \frac{(1-\vartheta^S)}{\vartheta^S} \frac{\kappa^S}{\kappa^M}.$$

Proof. See Appendix B.1. □

Proposition 1 establishes that the *relative* labor market tightness of the two sectors is constant in the steady-state equilibrium and characterizes its level. Asymmetric bargaining power and/or vacancy costs introduce a wedge in tightness between the two sectors. Conversely, if both the bargaining power and vacancy costs are symmetric, tightness is equal in the two sectors. The derivation of Proposition 1 (see Appendix B.1) builds on Ravn (2008), where a relationship between tightness and the marginal utility of consumption is derived in a one-sector search and matching model with endogenous participation.

The relationship between relative labor supply and relative labor demand directly follows from the proposition,

$$\underbrace{\frac{s}{1-s} \equiv \frac{u^M}{u^S}}_{\substack{\text{Relative labor}\\ \text{supply}}} = \frac{(1-\vartheta^M)}{\vartheta^M} \frac{\vartheta^S}{(1-\vartheta^S)} \frac{\kappa^M}{\kappa^S} \quad \underbrace{\frac{v^M}{v^S}}_{\substack{\text{Relative labor}\\ \text{demand}}}.$$

For a given level of relative labor demand (which depends, among others, on the degree of automation ζ), the pool of job seekers in manufacturing increases with the relative (i) bargaining power of workers and (ii) vacancy cost. In the second case, an increased pool of unemployed is required to compensate for the higher vacancy cost when firms decide about new vacancies so that the level of labor demand is sustained in equilibrium.

Finally, notice that the household decides how to allocate job seekers by comparing the discounted expected values of searching in the two sectors, $\psi^{j,h} \beta E_t \left[V^h_{n^j{t+1}} \right]$, which, in turn, is equal to the probability of finding a job times the discounted expected value of being employed. The optimal value s_t^* is given by,

$$s_t^* = \begin{cases} 1 & \psi_t^{M,h} \beta E_t \left[V^h_{n^M{t+1}} \right] > \psi_t^{S,h} \beta E_t \left[V^h_{n^S{t+1}} \right] \\ s_t^* \in (0,1) & \psi_t^{M,h} \beta E_t \left[V^h_{n^M{t+1}} \right] = \psi_t^{S,h} \beta E_t \left[V^h_{n^S{t+1}} \right] \\ 0 & \psi_t^{M,h} \beta E_t \left[V^h_{n^M{t+1}} \right] < \psi_t^{S,h} \beta E_t \left[V^h_{n^S{t+1}} \right]. \end{cases}$$

In the steady-state equilibrium, we can rule out the two corner solutions. If $s^* = 1$ and all the unemployed search in manufacturing, there is no production in services. Yet, as long as the two sectoral goods are not perfect substitutes in the final good production, the marginal product of the service good becomes infinite, leading to an infinite wage, which is incompatible with zero labor supply in this sector. If $s^* = 0$ and all the unemployed search in services, there is no production in manufacturing in the long run. Yet, as long as capital and labor are not perfect substitutes in manufacturing production, the marginal product of labor in manufacturing becomes infinite, which, again, is incompatible with a zero supply of labor in that sector. Therefore, the only possible solution is $s^* \in (0, 1)$.

3.4 Parameterization

In this section, we describe the calibration of the initial steady state, which we take to refer to the start year 1994 in the analysis of Dauth et al. (2021). We calibrate the model annually for the German economy. Some of the model parameters are taken from the literature. We choose the rest of the parameters to match a set of moments, using the simulated method of moments. Table 3.1 summarizes our parameterization.

Household. We use the data set built by Jordà et al. (2019) to compute the return to capital r in Germany, which is equal to 5% in 1994. We set the capital depreciation rate δ equal to 4%. To choose the value for the discount factor, we use the Euler equation in the steady state, $\beta = 1/(1 + r - \delta)$. For the inverse elasticity of the intertemporal substitution η, much of the literature uses econometric estimates between 0 and 2 (see, e.g., Hansen and Singleton, 1983). The estimated aggregate Frisch elasticity for Germany varies between 0.85 and 1.06 in a micro panel of men in Germany from 2000 to 2013 used by Kneip et al. (2020). We thus set the Frisch elasticity to 0.85 ($\phi = 2$). We have performed sensitivity analysis for different values $\phi = 4, 6$ (see Figure B.4 in Appendix B.7 and footnote 15). We calibrate the relative utility weight for leisure Φ to target a steady-state participation rate of 70%, in line with the data.

Production. To calibrate the parameters of the aggregate production function, we set the share of manufacturing output γ to 0.32 to match a sectoral output ratio of 0.891, measured by the ratio of value added in manufacturing and services in 1994. We set the elasticity of substitution between the two sectoral goods χ to 0.3, as in Ngai and Pissarides (2007). We set the weight attached to capital versus labor in manufacturing ζ by targeting the manufacturing capital share in 1994, which is equal to 0.19.[7] Similarly, we set the value for the weight of capital in the production of services ξ by targeting the capital share in the

[7]EUKLEMS defines the capital share as the ratio of capital services to value added. Following Iftikhar and Zaharieva (2019), we define our manufacturing sector as the aggregate of Industries A-F in the German WZ08 industry classification.

DESCRIPTION		VALUE	TARGET/SOURCE
HOUSEHOLD			
β	Discount factor	0.99	Return to capital, 5%
δ	Depreciation rate	0.04	Standard calibration
Φ	Relative utility from leisure	0.14	Participation Rate, 71%
ϕ	Inverse Frisch elasticity of labor supply	2	Kneip et al. (2020)
η	Inverse elasticity of intertemporal substitution	2	Hansen and Singleton (1983)
PRODUCTION			
χ	Manufacturing-services elasticity of substitution	0.3	Ngai and Pissarides (2007)
γ	Share of manufacturing in total output	0.32	Sectoral output ratio, 0.891
ζ	Weight attached to capital versus labor in manuf.	0.24	Capital share in manuf., 0.19
ξ	Weight attached to capital versus labor in services	0.36	Capital share in services, 0.28
α, ρ	Capital-labor elasticities of substitution	0.8	Knoblach et al. (2020)
LABOR MARKET			
θ^M, θ^S	Bargaining power of firms	0.43, 0.6	Iftikhar and Zaharieva (2019)
μ_1	Matching efficiency	0.58	Iftikhar and Zaharieva (2019)
μ_2	Elasticity of matching to vacancies	0.46	Literature
σ	Separation rate	0.08	Iftikhar and Zaharieva (2019)
κ	Vacancy cost	0.11	Share of the average wage, 20%
ϖ	Replacement rate	0.6	OECD data

Table 3.1: Parameterization

service sector in 1994, which is 0.28.[8] We set the elasticity of substitution between capital and labor in manufacturing and services, α and ρ, equal to 0.6. Based on a meta-regression sample, Knoblach et al. (2020) estimate a long-run elasticity for the aggregate economy in the range of 0.45-0.87, noting that most industrial estimates do not deviate significantly from the estimate for the aggregate economy. Oberfield and Raval (2020) find the US manufacturing sector's aggregate elasticity to be in the range of 0.5-0.7.

Labor Markets. To calibrate the parameters for the bargaining power of firms in each sector, we take weighted averages of the estimates for high-skill and low-skill workers in Iftikhar and Zaharieva (2019). A lower bargaining power for workers in the service sector is in line with the empirical evidence that service workers get a lower fraction of output produced in their sector, leading to a mild wage premium in manufacturing of around 2% in our calibration. The same authors estimate the average job duration rate in Germany to be 12.25 years, so we set the destruction rate in both sectors as $\sigma = 1/12.25 = 0.08$. We

[8] We calculate this value using EUKLEMS data for industries that are defined as "Market Economy", excluding the set of industries (A-F) that define our automatable sector (manufacturing).

set the gross replacement rate ϖ equal to 0.6.[9] For the vacancy cost parameter, we set in both sectors $\kappa = 0.1$, which implies that vacancy costs represent around 20% of the average wage. We set the matching efficiency parameter μ_1 equal to 0.58, in line with the estimate in Iftikhar and Zaharieva (2019). We also perform sensitivity analysis for $\mu_1 = 0.4, 0.5$ (see Figure B.5 in Appendix B.7). We set the elasticity of the matching function with respect to vacancies μ_2 equal to 0.46. This value is close to 0.5, often assumed in the search and matching literature, and also close to the estimate of 0.54 in Iftikhar and Zaharieva (2019), based on aggregate data of the Federal Employment Agency.

3.5 Automation and Sectoral Reallocation: Long-Run Analysis

In this section, we present the main results of our quantitative analysis.

3.5.1 Steady-State Results (Untargeted Moments)

Let us first report three side statistics to get an idea of the overall performance of our quantitative theory. In Table 3.2, we report the steady-state aggregate labor share, the aggregate unemployment rate, and the sectoral employment ratio. The overall picture that emerges shows that our model does a good job in providing satisfactory values for these side statistics.

VARIABLE	**EXPRESSION**	**MODEL**	**DATA**
Labor share: aggregate	$\frac{w^M n^M + w^S n^S}{Y}$	0.72	0.76
Unemployment rate	$\frac{u}{1-l}$	0.09	0.08
Labor ratio: manuf./services	$\frac{n^M}{n^S}$	0.99	0.86

Table 3.2: Steady-state results (untargeted moments)

3.5.2 Analysis Across Steady States

Next, we discuss steady-state comparative statics with respect to an increase in the degree of automation ζ. Figure 3.4 depicts the results for the main variables in the model for $0.24 < \zeta < 0.45$. The lower limit for ζ is the same as in Table 3.1. The upper limit for ζ is chosen by targeting a manufacturing capital share of 0.34 in 2014, which is the end year in the empirical analysis of Dauth et al. (2021).

[9]According to the OECD, the standard rates in Germany after 2000 are 60% of the previous earnings net of tax.

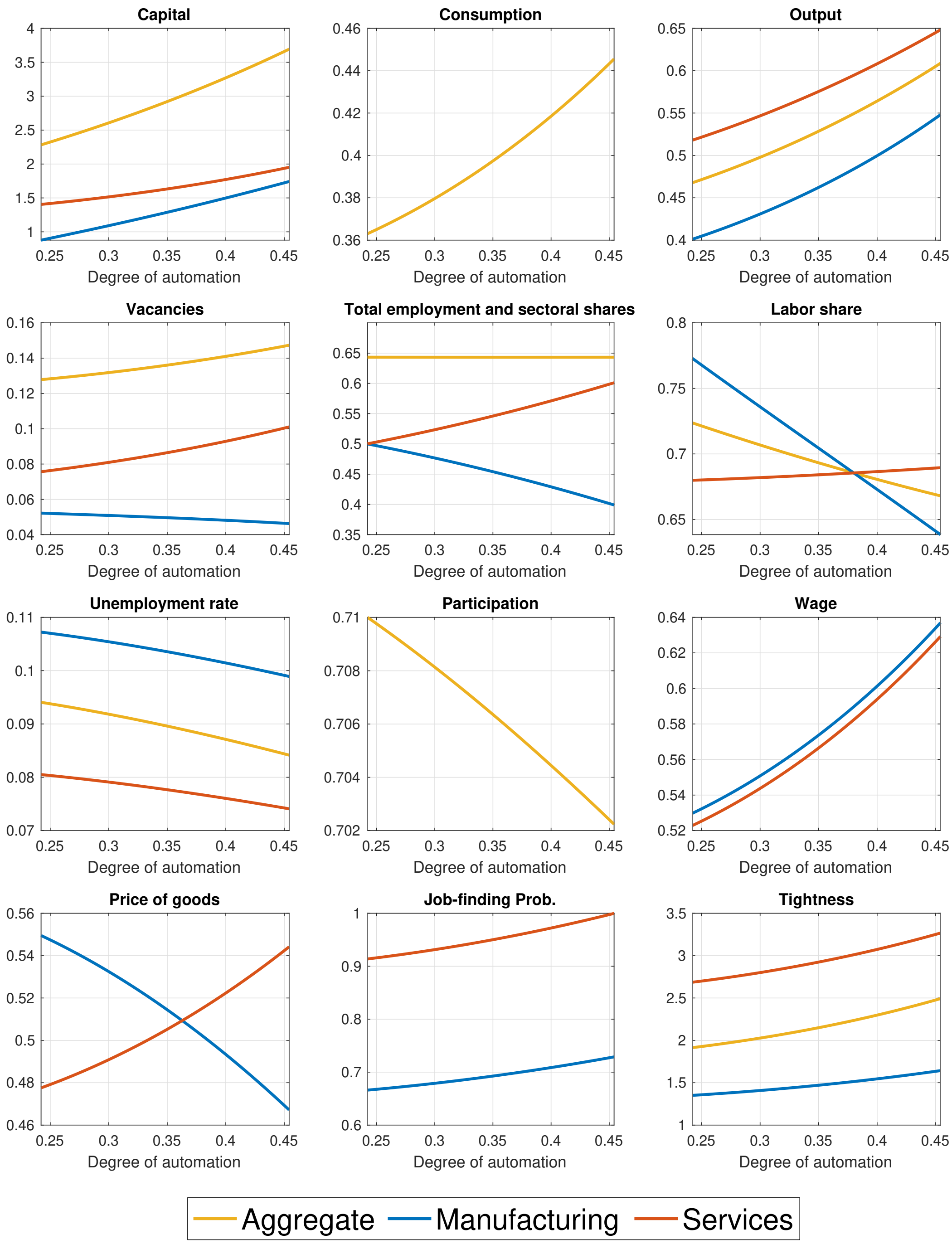

Figure 3.4: Steady-state effects of automation in a two-sector economy

Note: The y-axis shows steady-state levels.

Sectoral Reallocation of Output. A higher degree of automation ζ corresponds to an increased (decreased) capital (labor) intensity of manufacturing production. Therefore, an increase in ζ reduces the importance of the limiting factor, labor, in the production of the manufacturing good and the capital demand of the manufacturing sector increases. Since the steady-state return to capital is constant, while the steady-state return to labor can freely adjust, the capital increase due to a higher ζ dominates the labor decline. Therefore, manufacturing output increases.[10] Also, the level of output in services increases. Therefore, the economy experiences an aggregate output expansion. Overall, a higher ζ increases the steady-state ratio of manufacturing to service output M/S and decreases the relative price of the manufacturing good (see equations (3.17) and (3.18)).

Consumption, Participation, and Labor Share. The positive effect on aggregate income explains the increase in consumption and the decrease of participation in the long run. Automation has a negative effect on the aggregate labor income share, which is driven by the manufacturing sector and is in line with the previous evidence from the literature on the importance of the automation mechanism for a countercyclical labor share (see, e.g., Bergholt et al., 2021; Leduc and Liu, 2020b).

Sectoral Reallocation of Labor. Vacancies in the manufacturing sector decrease. Automation affects labor demand in manufacturing through two competing channels: (a) production becomes less labor-intensive, which tends to decrease employment *(labor-intensity channel)* and (b) since capital and labor are complements, the increase in capital tends to increase labor demand *(capital-labor complementarity effect)*. Vacancies in services increase due to the expansion in the demand for services. Total vacancies increase as well.

The number of unemployed searchers drops in the manufacturing sector as households reduce participation and reallocate job search towards services. The unemployment rate drops in the service sector too, but the share of searchers increases (see blue line in Figure 3.5). Total unemployment falls.

Labor market tightness increases in both sectors. The effect on the hiring rates follows from the fact that they are a positive function of tightness (while the opposite holds for vacancy-filling rates). The impact of automation on wages in both sectors is positive, consistently with the decrease in the vacancy-filling probabilities.

[10] The effect of an increase in ζ on manufacturing output M is expressed by the derivative:

$$\frac{\partial M}{\partial \zeta} = \frac{1}{\alpha} M^{(1-\alpha)} \left[(k^M)^\alpha - (n^M)^\alpha + \zeta \alpha \frac{\partial k}{\partial \zeta} + (1-\zeta)\alpha \frac{\partial n^M}{\partial \zeta} \right]$$

An increase in ζ induces an accumulation of capital ($\frac{\partial k^M}{\partial \zeta} > 0$) in the long run and a decrease in employment ($\frac{\partial n^M}{\partial \zeta} < 0$). The difference $(k^M)^\alpha - (n^M)^\alpha$ also matters for which effect dominates. If the initial value of ζ is sufficiently low, the steady-state capital stock k^M is relatively low and labor n^M is relatively more important in the production, leading to a decrease in manufacturing output.

Figure 3.5: Steady-state effect of automation on searchers' share in manufacturing

Note: The y-axis shows steady-state levels. The blue line refers to the baseline model, whereas the red line refers to a model variant where the sectoral allocation of job seekers is kept fixed.

Following the sectoral reallocation of labor, employment increases in services and falls in manufacturing in such a way that aggregate employment remains relatively constant, in line with the empirical evidence in Dauth et al. (2021). The pattern matches well the one observed in Figure 3.1.

In sum, labor markets adjust to automation through vacancy creation, sectoral reallocation of the unemployed, and participation. The findings also highlight the expansionary effects of automation on the economy, namely the aggregate output expansion and unemployment reduction.

3.5.3 Reproducing the Size of the Shift in Key Variables

To assess how well our model can explain the sectoral reallocation of employment in Germany, we focus next on comparing two steady states in Table 3.3, namely with $\zeta = 0.24$ (targeting a manufacturing capital share equal to 0.19 in 1994) and $\zeta = 0.45$ (targeting a manufacturing capital share equal to 0.34 in 2014).

Let us first examine the steady-state values for the ratio of manufacturing employment to service employment for these two values of ζ. The model predicts a decline of 34% in the ratio of manufacturing employment to service employment, which is reasonably close to the one found in the aggregate data for the German economy (30%). Turning next to the aggregate labor share, the model predicts a fall of 7.7%, which is extremely close to the value in the data (7%). For the labor share in manufacturing, the model predicts a

VARIABLE	EXPRESSION	STEADY STATE 1	STEADY STATE 2	CHANGE: MODEL	CHANGE: DATA
Degree of automation	ζ	0.24	0.45	88%	N/A
Manuf. capital share	$\frac{rK^M}{p^M M}$	0.19	0.34	71%	71%
Sectoral labor ratio	$\frac{n^M}{n^S}$	0.99	0.66	-34%	-30%
Labor share: aggregate	$\frac{w^M n^M + w^S n^S}{Y}$	0.72	0.67	-7.7%	-7%
Labor share: services	$\frac{w^S n^S}{p^S S}$	0.68	0.69	1.4%	0%
Labor share: manuf.	$\frac{w^M n^M}{p^M M}$	0.77	0.64	-17.4%	-18%

Table 3.3: Changes between two steady states and model fit to data

Note: In steady state 1 and steady state 2, the degree of automation ζ is set to target the capital share in German manufacturing in 1994 and 2014, respectively. The change in the manufacturing capital share in the model and data is therefore the same by construction.

decline of 17.4%, which again matches well with the observed change in the data (18%). Finally, for the labor share in services, the model predicts a small increase of 1.4%, while in the data the change is essentially zero.

Overall, the model can reproduce satisfactorily the magnitude of the decline in the labor share and in the ratio of manufacturing employment to service employment in Germany between 1994 and 2014.

3.6 What Determines the Extent of Sectoral Reallocation?

In this section, we investigate the role of key parameters and features of the model, namely (i) the elasticity of substitution between the sectoral goods, (ii) the elasticity of substitution between capital and labor in the automatable sector, and (iii) the sectoral mobility of job seekers.

3.6.1 Elasticities of Substitution

Between the Sectoral Goods. The elasticity of substitution between the sectoral goods χ matters for the sectoral reallocation of output and labor. Figure 3.6 compares the change in key sectoral ratios of variables as the degree of automation ζ increases from the initial steady state (with $\zeta = 0.24$) for a higher elasticitity χ and for our benchmark calibration. Additional variables and the same results in levels of these ratios are included in Appendix B.7. Relative to the baseline calibration ($\chi = 0.3$), when we increase the elasticity ($\chi = 1.5$), the sectoral output ratio M/S changes by more due to automation because it is easier now to substitute services by manufacturing intermediate goods in the final good production. Even when manufacturing and services are gross substitutes ($\chi = 1.5$), output in services increases.[11] This is because of two different effects that have the same sign in our baseline calibration and opposite signs when we increase χ.

Firstly, the changes in the demand for services and manufacturing goods are affected by the standard income and substitution effects due to a change in the relative price of the manufacturing good. On the one hand, the increase in automation and the accumulation of capital leads to a decrease in the marginal cost of production in manufacturing, given the constant rental rate of capital in steady state. That is, the relative price of the manufacturing good relative to services in the production of the final good decreases.[12] This implies a negative substitution effect on the use of services in the final good production. On the other hand, the reduction in the cost of manufacturing has a positive income effect for both inputs in the final good sector. In our baseline calibration, the positive income effect dominates, while with higher χ the negative substitution effect dominates, as can be seen in the evolution of the expenditure ratio for manufacturing and service goods in the upper left panel of Figure 3.6.

Secondly, the increase in the capital stock (which represents household wealth) due to automation in the long run generates a positive wealth effect that increases the demand for services and manufacturing goods. This second effect leads to an increase in service production for both calibrations, despite the fact that manufacturing and services are gross substitutes if $\chi > 1$.

However, the stronger substitution effect reduces the degree of sectoral reallocation if the elasticity of substitution is higher, despite an overall increase in service production. Consequently, an increase in χ mitigates the effect of automation on the sectoral reallocation of output, labor, vacancies, and job seekers (see the plots of the sectoral labor ratios n^M/n^S, v^M/v^S, and u^M/u^S). In line with these results, the drop in the wage premium in manufacturing w^M/w^S becomes less pronounced and total employment decreases.[13]

Between Capital and Labor in the Automatable Sector. The elasticity of substitution between capital and labor in manufacturing matters for the sectoral reallocation of labor. Figure 3.6 also depicts results for a lower value of this elasticitity ($\alpha = 0.7$). Through the capital-labor complementarity channel, a decrease in α tends to dampen the automation-driven sectoral reallocation of vacancies, job seekers, and labor as well as the

[11] See the upper middle panel of Figure B.1 in Appendix B.7.

[12] We show an empirical counterpart of the relative prices for manufacturing and services in Figure B.6 of Appendix B.7.

[13] See Figure B.1 in Appendix B.7.

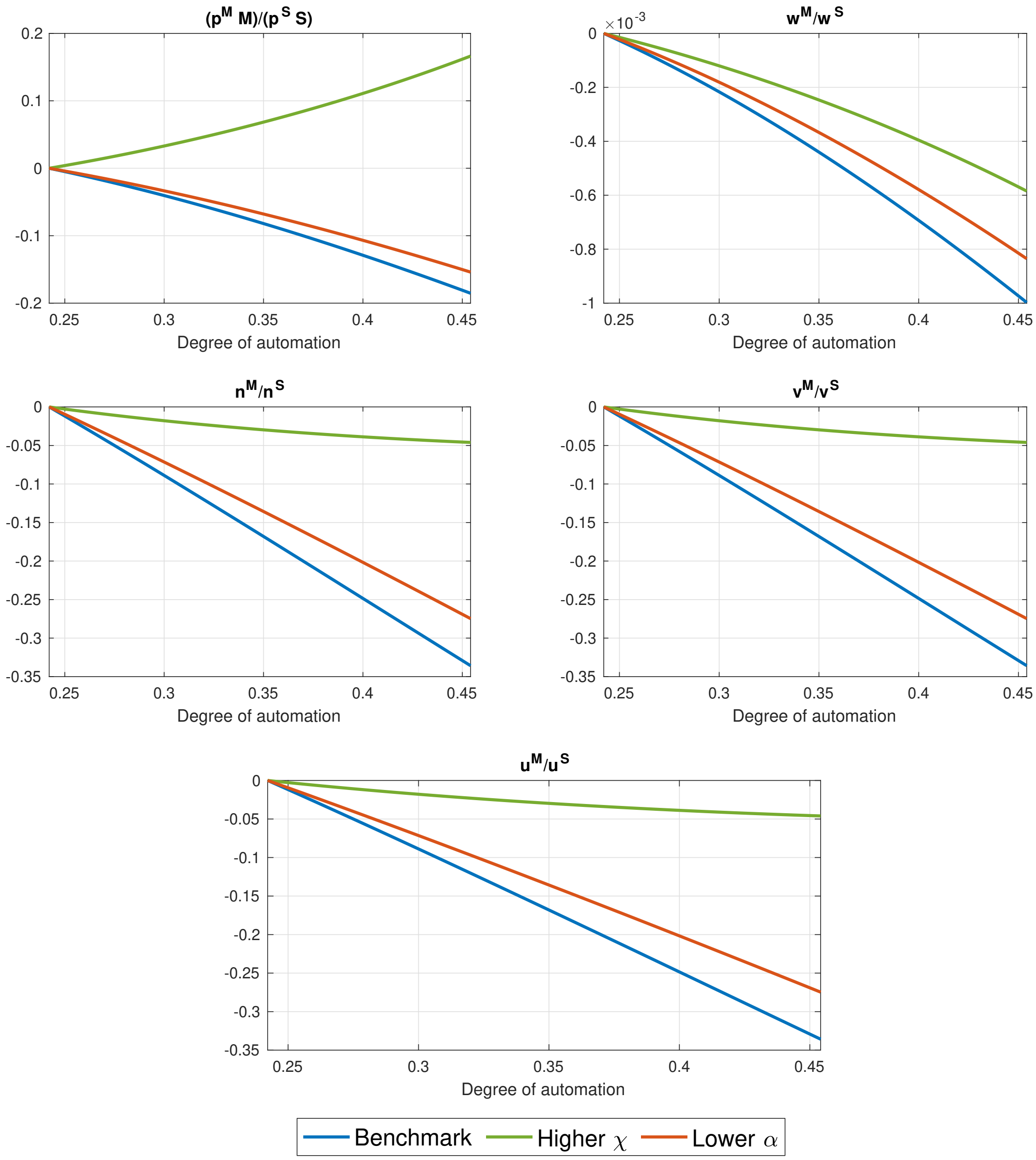

Figure 3.6: Steady-state effects of automation in a two-sector economy: Different elasticities of substitution between capital and labor ($\alpha = 0.7$) and between the two sectoral goods ($\chi = 1.5$)

Note: All the plotted variables are normalized to zero in the initial steady state. We denote the ratios of manufacturing to services variables as follows: $p^M M/p^S S$ *for the value of output,* w^M/w^S *for wages,* n^M/n^S *for labor,* v^M/v^S *for vacancies, and* u^M/u^S *for job seekers.*

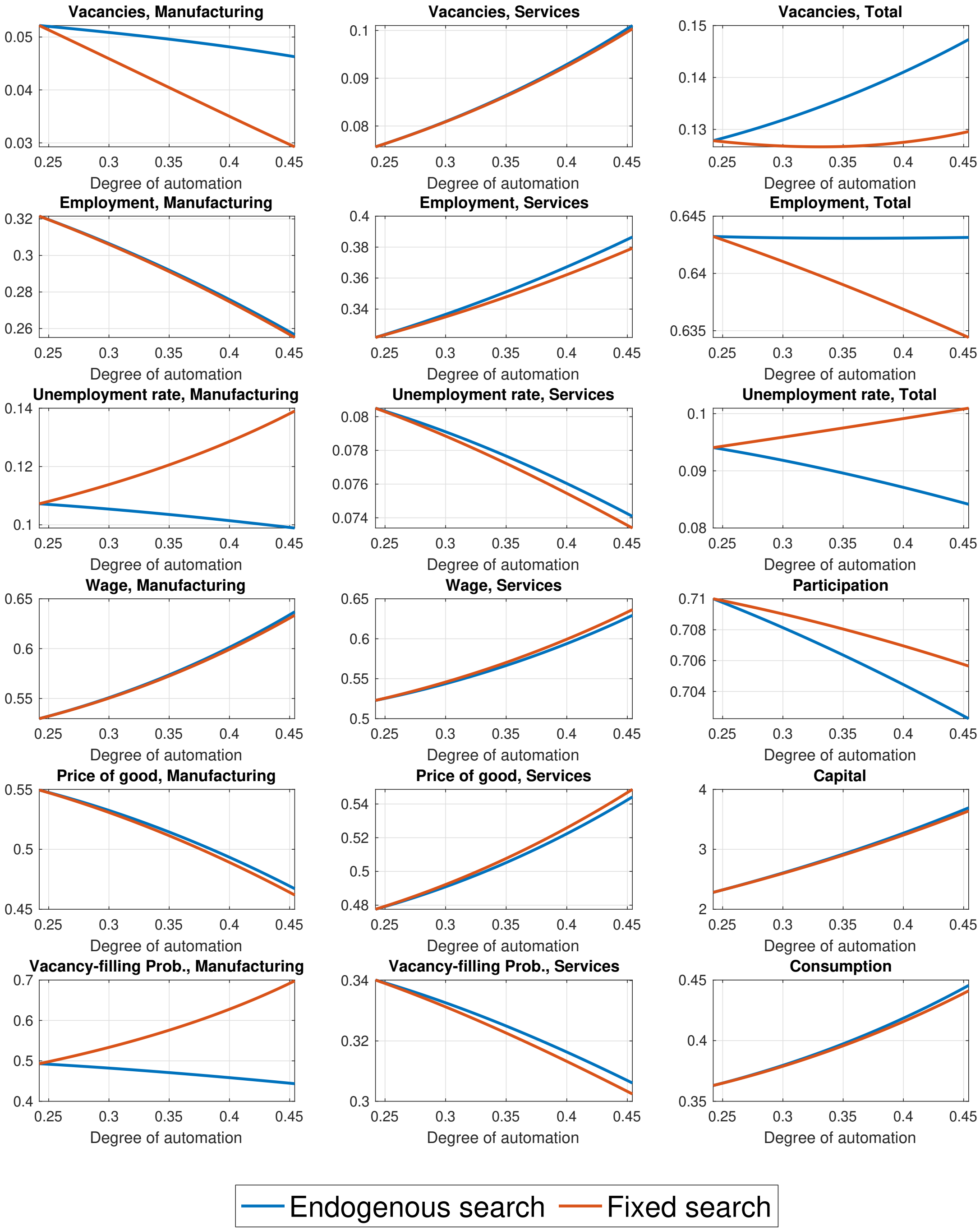

Figure 3.7: Steady-state effects of automation with and without sectoral mobility

Note: The y-axis shows steady-state levels. The blue line refers to the baseline model, whereas the red line refers to a model variant where the sectoral allocation of job seekers is kept fixed.

drop in the wage premium in manufacturing (see the plots of the sectoral labor ratios v^M/v^S, u^M/u^S, n^M/n^S, and w^M/w^S).

3.6.2 Sectoral Mobility of Job Seekers

Last, we explore the extent to which shutting down the reallocation of job seekers between the two sectors affects our findings. We examine the comparative statics with (a) endogenous sector-specific search (as in the baseline model) and (b) fixed sectoral shares of job seekers by keeping the share of searchers in manufacturing s equal to the value it attains endogenously in the initial steady state with $\zeta = 0.24$ (see Figure 3.5). In other words, equation (3.13) is no longer used. Hence, although the number of employees per sector can evolve separately through the dynamics of vacancy postings, matches, and participation, households cannot freely reallocate job seekers between sectors.

With a fixed sectoral allocation of job seekers, as we move from a steady state with $\zeta = 0.24$ to a steady state with $\zeta = 0.45$ (in line with Table 3.3), total employment decreases, rather than remaining constant as with endogenous allocation (see Figure 3.7).[14] If job seekers cannot switch sector, the unemployment rate in manufacturing increases with ζ, driving an increase in total unemployment. At the same time, the decrease in the unemployment rate in services becomes sharper since there is less job competition in this market without the sectoral reallocation of job seekers. Finally, the sectoral mobility of job seekers also matters for the effect of automation on manufacturing vacancies with the decline becoming stronger under fixed search. The positive wealth effect for the household (increase in consumption and decrease in participation) is weakened under fixed search.[15]

3.7 Conclusion

The paper studies the sectoral impact of automation through the lens of a general equilibrium model with matching frictions, endogenous participation, and two sectors. As in empirical evidence from Germany (see Dauth et al., 2021), automation induces firms to create fewer new vacancies and job seekers to search less in the robot-exposed sector. Analysis across steady states shows that the reduction in manufacturing employment from automation can be offset by the increased service employment, thus leaving aggregate employment unaffected. The model does a good job in replicating (a) qualitatively the empirical evolution of employment and labor compensation in manufacturing and services, and (b) the magnitude of the decline in the aggregate labor share and the ratio of manufacturing employment to service employment between 1994 and 2014.

Our model can be extended along several dimensions. For instance, the good produced in the automated sector (manufacturing) is, in fact, a tradable good. One plausible extension could therefore be to consider the sectoral impact of automation in an open economy framework. Another interesting avenue for further research would be to introduce skill heterogeneity and capital-skill complementarity (see, e.g., Dolado et al., 2021, Santini, 2021). Such a setup could capture the idea that robots are complements with high-skill workers

[14] Figure 3.7 omits the output and labor share variables as the differences between the two model variants are minimal. Results are available upon request.

[15] In Appendix B.7, we also show results for different values of the parameter governing the Frisch elasticity of labor supply ($\phi = 4, 6$, see Figure B.4). A lower value of the Frisch elasticity (higher value of ϕ) matters for the steady-state levels of the variables but without affecting our main results.

but substitutes for low-skill workers, allowing to study implications for inequality. We leave these topics for future research.

Bibliography

Daron Acemoglu and Pascual Restrepo. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542, 2018.

Daron Acemoglu and Pascual Restrepo. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244, 2020.

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

Philippe Aghion, John Van Reenen, and Luigi Zingales. Innovation and institutional ownership. *American economic review*, 103(1):277–304, 2013.

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

Esteve Almirall and Ramon Casadesus-Masanell. Open versus closed innovation: A model of discovery and divergence. *Academy of management review*, 35(1):27–47, 2010.

Massimo Anelli, Italo Colantone, and Piero Stanig. We Were the Robots: Automation and Voting Behavior in Western Europe. 2020.

Miguel Antón, José Azar, Mireia Giné, and Luca Xianran Lin. Beyond the Target: M&A Decisions and Rival Ownership. 2021a.

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

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

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

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

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

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

Kenneth J. Arrow. 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*, pages 609–626. 1962.

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

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

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

José Azar, Sahil Raina, and Martin C. Schmalz. Ultimate Ownership and Bank Competition. 2019.

José Azar, Martin C. Schmalz, and Isabel Tecu. Research on the Competitive Consequences of Common Ownership: A Methodological Critique. 2021.

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

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

Matthew Backus, Christopher Conlon, and Michael Sinkinson. Common Ownership and Competition in the Ready-To-Eat Cereal Industry. 2021.

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

Benjamin Balsmeier, Lee Fleming, and Gustavo Manso. Independent boards and innovation. *Journal of Financial Economics*, 123(3):536–557, 2017.

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

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

Andrew Berg, Edward F Buffie, and Luis-Felipe Zanna. Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics*, 97:117–148, 2018.

Drago Bergholt, Francesco Furlanetto, and Nicolò Maffei-Faccioli. The decline of the labor share: New empirical evidence. *American Economic Journal: Macroeconomics*, 2021.

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

Marianne Bertrand and Sendhil Mullainathan. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of political Economy*, 111(5):1043–1075, 2003.

Marshall E. Blume, Donald B. Keim, et al. The changing nature of institutional stock investing. *Critical Finance Review*, 6:1–41, 2014.

Alice Bonaime, Huseyin Gulen, and Mihai Ion. Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, 129(3):531–558, 2018.

Audra L. Boone and Joshua T. White. The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, 117(3):508–533, 2015.

Alon Brav, Wei Jiang, Frank Partnoy, and Randall Thomas. Hedge fund activism, corporate governance, and firm performance. *The Journal of Finance*, 63(4):1729–1775, 2008.

Alon Brav, Wei Jiang, Tao Li, and James Pinnington. Picking friends before picking (proxy) fights: How mutual fund voting shapes proxy contests. *Columbia Business School Research Paper*, (18-16), 2020.

Chris Brooks, Zhong Chen, and Yeqin Zeng. Institutional cross-ownership and corporate strategy: The case of mergers and acquisitions. *Journal of Corporate Finance*, 48:187–216, 2018.

Brian J. Bushee. The influence of institutional investors on myopic r&d investment behavior. *Accounting review*, pages 305–333, 1998.

Yen-Cheng Chang, Harrison Hong, and Inessa Liskovich. Regression discontinuity and the price effects of stock market indexing. *The Review of Financial Studies*, 28(1):212–246, 2015.

Tao Chen, Jarrad Harford, and Chen Lin. Do analysts matter for governance? evidence from natural experiments. *Journal of financial Economics*, 115(2):383–410, 2015.

Henry William Chesbrough. *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press, 2003.

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

Dario Cords and Klaus Prettner. Technological unemployment revisited: Automation in a search and matching framework. Technical report, Global Labor Organization (GLO) Discussion Paper, No. 308, 2019.

Adrian Aycan Corum, Andrey Malenko, and Nadya Malenko. Corporate governance in the presence of active and passive delegated investment. *European Corporate Governance Institute–Finance Working Paper*, 695, 2021.

Alan D. Crane, Sébastien Michenaud, and James P. Weston. The effect of institutional ownership on payout policy: Evidence from index thresholds. *The Review of Financial Studies*, 29(6):1377–1408, 2016.

Henrik Cronqvist and Rüdiger Fahlenbrach. Large shareholders and corporate policies. *The Review of Financial Studies*, 22(10):3941–3976, 2008.

Edgar Cruz and Xavier Raurich. Leisure time and the sectoral composition of employment. *Review of Economic Dynamics*, 38:198–219, 2020.

Wolfgang Dauth, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. The adjustment of labor markets to robots. *Journal of the European Economic Association*, forthcoming, 2021.

Patrick Dennis, Kristopher Gerardi, and Carola Schenone. Common Ownership Does Not Have Anti-Competitive Effects in the Airline Industry. 2019.

François Derrien, Ambrus Kecskés, and David Thesmar. Investor horizons and corporate policies. *Journal of Financial and Quantitative Analysis*, 48(6):1755–1780, 2013.

Juan J. Dolado, Florentino Felgueroso, and Juan F. Jimeno. The Spanish Labour Market at the Crossroads: Covid-19 meets the Megatrends. 2020.

Juan J. Dolado, Gergö Motyovszki, and Evi Pappa. Monetary policy and inequality under labor market frictions and capital-skill complementarity. *American Economic Journal: Macroeconomics*, 13:292–332, 2021.

Anne Duchêne, Debapriya Sen, and Konstantinos Serfes. Patent Licensing and Entry Deterrence: The Role of Low Royalties. *Economica*, 82:1324–1348, 2015.

Alexander Dyck, Adair Morse, and Luigi Zingales. Who blows the whistle on corporate fraud? *The Journal of Finance*, 65(6):2213–2253, 2010.

Maya Eden and Paul Gaggl. On the welfare implications of automation. *Review of Economic Dynamics*, 29:15–43, 2018.

Alex Edmans, Itay Goldstein, and Wei Jiang. The real effects of financial markets: The impact of prices on takeovers. *The Journal of Finance*, 67(3):933–971, 2012.

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

Federal Trade Commission. Patent Assertion Entity Activity. An FTC Study. Technical report, 2016.

Eliezer M. Fich, Jarrad Harford, and Anh L. Tran. Motivated monitors: The importance of institutional investors' portfolio weights. *Journal of Financial Economics*, 118(1):21–48, 2015.

Nicolás Figueroa and Carlos J. Serrano. Patent trading flows of small and large firms. *Research Policy*, 48(7):1601–1616, 2019.

Simona Frazzani, Kletia Noti, Maarten P. Schinkel, Jo Seldeslachts, Albert Banal-Estañol, Nuria Boot, and Carlo Angelici. Barriers to Competition through Joint Ownership by Institutional Investors. Technical Report May, 2020.

Nancy T. Gallini. Deterrence by Market Sharing: A Strategic Incentive for Licensing. *The American Economic Review*, 74(5):931–941, 1984.

Nancy T. Gallini and Brian D. Wright. Technology Transfer under Asymmetric Information. *The RAND Journal of Economics*, 21(1):147–160, 1990.

José-Miguel Gaspar, Massimo Massa, and Pedro Matos. Shareholder investment horizons and the market for corporate control. *Journal of financial economics*, 76(1):135–165, 2005.

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

Georg Graetz and Guy Michaels. Robots at work. *Review of Economics and Statistics*, 100(5):753–768, 2018.

Jillian Grennan, Roni Michaely, and Christopher J. Vincent. The deleveraging of US firms and institutional investors' role. *Available at SSRN 1941902*, 2017.

Francesco Grigoli, Zsoka Koczan, and Petia Topalova. Automation and labor force participation in advanced economies: Macro and micro evidence. *European Economic Review*, page 103443, 2020.

Gene M. Grossman and Elhanan Helpman. Quality ladders in the theory of growth. *The review of economic studies*, 58(1):43–61, 1991.

Sanford J. Grossman and Oliver D. Hart. Takeover Bids, The Free-Rider Problem, and the Theory of the Corporation. *The Bell Journal of Economics*, 11(1):42–64, 1980.

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

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

Lars Peter Hansen and Kenneth J. Singleton. Stochastic consumption, risk aversion, and the temporal behavior of asset returns. *Journal of Political Economy*, 91:249–265, 1983.

Jarrad Harford, Dirk Jenter, and Kai Li. Institutional cross-holdings and their effect on acquisition decisions. *Journal of Financial Economics*, 99(1):27–39, 2011.

Jarrad Harford, Ambrus Kecskés, and Sattar Mansi. Do long-term investors improve corporate decision making? *Journal of Corporate Finance*, 50:424–452, 2018.

Oliver D. Hart. The market mechanism as an incentive scheme. *The Bell Journal of Economics*, pages 366–382, 1983.

Jie He and Jiekun Huang. Product market competition in a world of cross-ownership: Evidence from institutional blockholdings. *Review of Financial Studies*, 30(8):2674–2718, 2017.

Jie (Jack) He and Xuan Tian. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109:856–878, 2013.

Jie (Jack) He, Jiekun Huang, and Shan Zhao. Internalizing governance externalities: The role of institutional cross-ownership. *Journal of Financial Economics*, 134(2):400–418, 2019.

Davidson Heath, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg. Do index funds monitor? *The Review of Financial Studies*, 35(1):91–131, 2022.

James J. Heckman. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161, 1979.

Berthold Herrendorf, Richard Rogerson, and Akos Valentinyi. Growth and structural transformation. In *Handbook of economic growth*, volume 2, pages 855–941. Elsevier, 2014.

Bengt Holmström. Managerial incentive problems: A dynamic perspective. *The review of Economic studies*, 66(1):169–182, 1999.

Zainab Iftikhar and Anna Zaharieva. General equilibrium effects of immigration in Germany: Search and matching approach. *Review of Economic Dynamics*, 31:245–276, 2019.

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

Peter Iliev, Jonathan Kalodimos, and Michelle Lowry. Investors' Attention to Corporate Governance. *Review of Financial Studies (forthcoming)*, 2020.

Nir Jaimovich, Itay Saporta-Eksten, Henry E. Siu, and Yaniv Yedid-Levi. The macroeconomics of automation: Data, theory, and policy analysis. Technical report, National Bureau of Economic Research, 2020.

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

Òscar Jordà, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M. Taylor. The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics*, 134 (3):1225–1298, 2019.

Steven N. Kaplan and Bernadette Minton. How has CEO turnover changed? increasingly performance sensitive boards and increasingly uneasy CEOs, 2006.

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

Michael L. Katz and Carl Shapiro. On the Licensing of Innovations. *The RAND Journal of Economics*, 16(4):504, 1985.

Pauline Kennedy, Daniel P. O'Brien, Minjae Song, and Keith Waehrer. The Competitive Effects of Common Ownership: Economic Foundations and Empirical Evidence. 2017.

Gary King and Richard Nielsen. Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, 27(4):435–454, 2019.

Alois Kneip, Monika Merz, and Lidia Storjohann. Aggregation and labor supply elasticities. *Journal of the European Economic Association*, 18(5):2315–2358, 2020.

Michael Knoblach, Martin Roessler, and Patrick Zwerschke. The elasticity of substitution between capital and labour in the US economy: A meta-regression analysis. *Oxford Bulletin of Economics and Statistics*, 82(1):62–82, 2020.

Camelia M. Kuhnen. Business Networks, Corporate Governance, and Contracting in the Mutual Fund Industry. *The Journal of Finance*, LXIV(5):2185–2220, 2009.

Jung H. Kwon, Haemin Dennis Park, and Shu Deng. When Do Firms Trade Patents? *Organization Science*, pages 1–20, 2021.

Sylvain Leduc and Zheng Liu. Can pandemic-induced job uncertainty stimulate automation? Federal Reserve Bank of San Francisco, 2020a.

Sylvain Leduc and Zheng Liu. Robots or workers? a macro analysis of automation and labor markets. Federal Reserve Bank of San Francisco, 2020b.

Miguel Leon-Ledesma and Alessio Moro. The rise of services and balanced growth in theory and data. *American Economic Journal: Macroeconomics*, 12(4):109–46, 2020.

Benjamin Lerch. Robots and Nonparticipation in the US: Where Have All the Displaced Workers Gone? *Available at SSRN 3650905*, 2020.

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

Xiaoxia Lou and Albert Y. Wang. Flow-induced trading pressure and corporate investment. *Journal of Financial and Quantitative Analysis*, 53(1):171–201, 2018.

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

Andrey Malenko and Nadya Malenko. Proxy advisory firms: The economics of selling information to voters. *The Journal of Finance*, 74(5):2441–2490, 2019.

Gregor Matvos and Michael Ostrovsky. Cross-ownership, returns, and voting in mergers. *Journal of Financial Economics*, 89(3):391–403, 2008.

Daniel McFadden. Conditional logit analysis of qualitative choice behavior. In P Zarembka, editor, *Frontiers of Econometrics*, pages 105–142. Academic Press, New York, NY, 1974.

Melissa Newham, Jo Seldeslachts, and Albert Banal-Estañol. Common Ownership and Market Entry: Evidence from the Pharmaceutical Industry. 2019.

L. Rachel Ngai and Christopher A. Pissarides. Structural change in a multisector model of growth. *American Economic Review*, 97(1):429–443, 2007.

L. Rachel Ngai and Christopher A Pissarides. Trends in hours and economic growth. *Review of Economic Dynamics*, 11(2):239–256, 2008.

Ezra Oberfield and Devesh Raval. Micro data and macro technology. *Econometrica*, forthcoming, 2020.

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

OECD. Common Ownership by Institutional Investors and its Impact on Competition: OECD Background Paper. Technical report, 2017.

D. J. Pederson. Blockholder attention. *Rutgers School of Business*, 2014.

Michael E. Porter. Capital disadvantage: America's failing capital investment system. *Harvard business review*, 70(5):65–82, 1992.

Romanos Priftis and Kirill Shakhnov. Sectoral reallocation: Long-run trends and short-run fluctuations of the last 150 years. *mimeo*, 2020.

Morten O. Ravn. The consumption-tightness puzzle. In *NBER International Seminar on Macroeconomics 2006*, pages 9–63. University of Chicago Press, 2008.

Pascual Restrepo. Skill mismatch and structural unemployment. 2015.

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

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

Jeffrey D. Sachs, Seth G. Benzell, and Guillermo LaGarda. Robots: Curse or blessing? a basic framework. *mimeo*, 2019.

Sampsa Samila, Markus Simeth, and David Wehrheim. Institutional ownership and the nature of corporate innovation. *Available at SSRN 3804417*, 2021.

Tommaso Santini. Automation with heterogeneous agents: The effect on consumption inequality. *mimeo*, 2021.

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

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

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

Carlos J. Serrano. The dynamics of the transfer and renewal of patents. *RAND Journal of Economics*, 41(4):686–708, 2010.

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

Carl Shapiro. Patent Licensing and R&D Rivalry. *The American Economic Review Papers and Proceedings*, 75(2):25–30, 1985.

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

Andrei Shleifer and Robert W. Vishny. Large Shareholders and Corporate Control. *Journal of Political Economy*, 94(3):461–488, 1986.

Jeremy C. Stein. Takeover threats and managerial myopia. *Journal of political economy*, 96(1):61–80, 1988.

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

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

Charles Ward, Chao Yin, and Yeqin Zeng. Institutional investor monitoring motivation and the marginal value of cash. *Journal of Corporate Finance*, 48:49–75, 2018.

Malcolm Wardlaw. Measuring mutual fund flow pressure as shock to stock returns. *The Journal of Finance*, 75(6):3221–3243, 2020.

Appendices

Appendix A

Common Ownership and the Market for Technology

A.1 Derivation of firms' objective function (2.1)

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:

$$\max \sum_i \gamma_{ij} W_i = \max \sum_i \gamma_{ij} \sum_l \beta_{il} \mathit{\Pi}_l \tag{A.1}$$

$$= \max \sum_i \gamma_{ij} \beta_{ij} \mathit{\Pi}_j + \sum_i \gamma_{ij} \sum_{l \neq j} \beta_{il} \mathit{\Pi}_l \tag{A.2}$$

$$= \max \mathit{\Pi}_j \sum_i \gamma_{ij} \beta_{ij} + \sum_{l \neq j} \sum_i \gamma_{ij} \beta_{il} \mathit{\Pi}_l \tag{A.3}$$

$$\propto \max \mathit{\Pi}_j + \sum_{l \neq j} \frac{\sum_i \gamma_{ij} \beta_{il}}{\sum_i \gamma_{ij} \beta_{ij}} \mathit{\Pi}_l. \tag{A.4}$$

Denoting $\lambda_{jl} \equiv \frac{\sum_i \gamma_{ij} \beta_{il}}{\sum_i \gamma_{ij} \beta_{ij}}$ and considering firm $j = 0$ and firms $l \in \{1, 2\}$ yields equation (2.1).

A.2 Bargaining Power and Matching

In the analysis of the model in section 2.3.2, I assume that the contract is proposed by the technology provider, making a take-it-or-leave it offer. This implies that the technology provider has all the bargaining power. This assumption seems plausible, because for the concrete technology, i.e., the bundle of patents the provider owns, the assignor is a monopolist. In this section, I relax this assumption and allow for the assignees to have some bargaining power. A suitable approach is to analyze the environment as a two-sided matching model with contracts. In this kind of model, I can study all feasible stable matchings μ for the situation outlined in section 3.2.[1]

In our simple market for technology transfer, a matching is a function μ, such that $\mu(0) \in \{1, 2\}$, i.e., one of the potential assignees is matched to firm 0 and adopts the technology, and the other firm stays unmatched.[2] Suppose, for instance, firm 0 and firm 1 are matched and engage in technology transfer, while firm 2 is the outsider, that is, it is matched with itself. Then, the matching μ is the function, $\mu(0) = 1$, $\mu(1) = 0$, and $\mu(2) = 2$. An outcome is a tuple (μ, F), i.e., a matching μ and a fixed fee $F \geq 0$ payed by firm $\mu(0)$ to firm 0. An outcome of this market is stable if it is (i) individually rational:

$$\phi_0(\mu(0), F) \geq \tilde{\phi}_0, \tag{A.5}$$

$$\Pi_{\mu(0)}(0, F) \geq \tilde{\pi}_{\mu(0)}, \tag{A.6}$$

and (ii) there is no blocking pair. In this simple model, this means that there does not exist (μ', F') with $\mu'(0) \neq \mu(0)$ and $F' \geq 0$, such that:

$$\Pi_{\mu'(0)}(0, F') > \tilde{\pi}_{\mu'(0)} \quad \text{and} \tag{A.7}$$

$$\phi_0(\mu'(0), F') > \phi_0(\mu(0), F). \tag{A.8}$$

Denote F^o the fee that makes firm $\mu'(0)$ indifferent between buying or not buying the technology, i.e.,

$$\Pi_{\mu'(0)}(0, F^o) = \tilde{\pi}_{\mu'(0)}. \tag{A.9}$$

Since an adopter's profit decreases in the fixed fee, a blocking pair does not exist if and only if

$$\phi_0(\mu(0), F) \geq \phi_0(\mu'(0), F^o). \tag{A.10}$$

Then, we can rewrite (A.5) as

$$F \geq \frac{C - \lambda_{0\mu(0)} \Delta\pi_\mu(0)}{1 - \lambda_{0\mu(0)}}, \tag{A.11}$$

and (A.10) as

$$F \geq \frac{1}{1 - \lambda_{0\mu(0)}} (\Delta\pi_{\mu'(0)} - \lambda_{0\mu(0)} \Delta\pi_{\mu(0)}), \tag{A.12}$$

where I have used that, by (A.9), $F^o = \Delta\pi_{\mu'(0)}$.

[1]The model that follows is a simple case of an assignment game (Shapley and Shubik, 1972) since utility is transferable.

[2]In case firm 0 keeps the technology, we have $\mu(0) = 0$. This case, however, is not interesting for my empirical analysis and, therefore, I exclude it from further consideration in this section.

By (A.6) firm $\mu(0)$ finds it profitable to adopt the technology at a fixed fee F if and only if

$$F \leq \Delta\pi_{\mu(0)}. \tag{A.13}$$

Therefore, by combining (A.12) and (A.13), we see that a necessary condition for F to exist and for (μ, F) to be a stable outcome is that

$$\Delta\pi_{\mu(0)} \geq \Delta\pi_{\mu'(0)}. \tag{A.14}$$

That is, as in the model analyzed in section 2.3.2, only the firm that profits the most from the technology can become the adopter in equilibrium.

μ is indeed an equilibrium matching if, by (A.11), (A.12), and (A.13), there exists F, such that

$$F \in \left[\max\left\{\frac{C - \lambda_{0\mu(0)}\Delta\pi_{\mu(0)}}{1 - \lambda_{0\mu(0)}}, \frac{1}{1 - \lambda_{0\mu(0)}}(\Delta\pi_{\mu'(0)} - \lambda_{0\mu(0)}\Delta\pi_{\mu(0)})\right\}, \Delta\pi_{\mu(0)}\right]. \tag{A.15}$$

If the set in (A.15) is non-empty then there exists a continuum of competitive equilibria (μ, F) which contains the equilibrium described in section 2.3.2, in which $F = \Delta\pi_{\mu(0)}$, i.e., the seller-optimal equilibrium. In the buyer-optimal equilibrium, F is equal to the lower bound of the interval in (A.15), i.e., if the assignees have all the bargaining power. For any other distribution of bargaining power, F lies within the interior of the interval. As can be seen, the distribution of bargaining power does not change the equilibrium matching. If a technology transfer occurs, the firm with the higher increment in profits, $\Delta\pi_l$, $l = 1, 2$, becomes the assignee.

A.3 Business Stealing Effects

In this section of the Appendix, I discuss in more detail the impact of business stealing effects on the results in the model of common ownership and technology transfer introduced in section 3.2 and studied in section 2.3.2. Remember, that business stealing effects hurts a potential adopter if the other firm becomes the assignee and adopts the technology. That is, the outsider of the deal earns operational profits π_l^n, which are lower than its ex-ante profits if no technology transfer takes place, i.e., $\pi_l^n < \tilde{\pi}_l$.

I follow the same procedure of backward induction as in Section 2.3.2. As it is the case without business stealing effects, the fixed fee offered in the state S_2 to the second assignee, firm β, is given by $F^{S_2} = \pi_\beta^r - \tilde{\pi}_\beta$. Firm 0 offers a contract if F^{S_2} is larger or equal than what firm 0 looses due to the cost of technology transfer and the business stealing effect exerted on the other firm, which is $C + \lambda_{0\alpha}(\tilde{\pi}_\alpha - \pi_\alpha^n)$. At stage S_1 the contract depends on whether firm 0 finds it profitable to transfer the technology at stage S_2. If there is a contract at stage S_2 firm α earns π_α^n. If, on the other hand, there is no contract signed at

S_2, then its profits are $\tilde{\pi}_\alpha$. Therefore, F^{S_1} is given by

$$F^{S_1} = \mathit{\Delta}\pi_\alpha(\lambda_{0\alpha}) \equiv \begin{cases} \pi^r_\alpha - \pi^n_\alpha & \text{if} \quad \pi^r_\beta - \tilde{\pi}_\beta \geq C + \lambda_{0\alpha}(\tilde{\pi}_\alpha - \pi^n_\alpha) \\ \pi^r_\alpha - \tilde{\pi}_\alpha & \text{if} \quad \pi^r_\beta - \tilde{\pi}_\beta < C + \lambda_{0\alpha}(\tilde{\pi}_\alpha - \pi^n_\alpha). \end{cases} \tag{A.16}$$

Notice, that $\tilde{\pi}_\alpha - \pi^n_\alpha \geq 0$ and, therefore, $\mathit{\Delta}\pi_\alpha(\lambda_{0\alpha})$ is non-increasing in $\lambda_{0\alpha}$. To analyze the model, let us consider the conditions in which the assignor (firm 0) sells the technology to firm 1 to determine how the common ownership between firm 0 and firm 1, λ_{01}, influences this decision, given some λ_{02}.

We can distinguish three cases. First, consider **case 1** in which the assignor prefers to keep the technology to selling it to firm 2 at stage S_1, i.e.,

$$\phi_0(F_2^{S_1}) < \tilde{\phi}_0. \tag{A.17}$$

Then, it will never offer it to firm 2 at stage S_2 of the game, since $\phi_0(F_2^{S_1}) \geq \phi_0(F_2^{S_2})$ as can be seen from (A.16). Notice that $\tilde{\phi}_0$ increases in λ_{01}. Therefore, in a situation in which condition (A.17) holds, either firm 1 will be the assignee in equilibrium, or no technology transfer occurs. Thus, an increase in common ownership incentive λ_{01} can not change the identity of the adopter from firm 1 to firm 2.

In **case 2**, firm 0 does not want to sell the technology to firm 2 at S_2 (given firm 1 rejected the offer at S_1). However, it prefers to sell it to firm 2 at the first stage S_1 to keeping the technology, i.e.,

$$\phi_0(F_2^{S_1}) \geq \tilde{\phi}_0 > \phi_0(F_2^{S_2}). \tag{A.18}$$

Then, $F_1^{S_1} = \pi^r_1 - \tilde{\pi}_1$. In this case, firm 0 again decides to which firm to sell at the first stage by solving (2.5). Let $\pi^x_2 \in \{\pi^n_2, \tilde{\pi}_2\}$. Firm 0 prefers to offer the contract at stage 1 to firm 1 if

$$\pi^r_1 - \tilde{\pi}_1 + \lambda_{01}(\tilde{\pi}_1 - \pi^n_1) \geq \pi^r_2 - \pi^x_2 + \lambda_{02}(\pi^x_2 - \pi^n_2). \tag{A.19}$$

Given any λ_{02}, a higher λ_{01} makes it more likely for this inequality to hold since the left-hand side increases in λ_{01}. Notice, also, that holding λ_{02} constant implies that we do not have to consider the cases separately for which firm 0 wants to sell the technology to firm 1 at S_2. The reason is that it does not depend on λ_{01}, but only on λ_{02}, if the outside option of rejecting the contract at S_1 for firm 2 is π^n_2 or $\tilde{\pi}_2$, as can be seen from (A.16).

Finally, in **case 3** firm 0 prefers to sell to firm 2 at any stage to keeping the technology, i.e., $\phi_0(F_2^{S_1}) \geq \phi_0(F_2^{S_2}) \geq \tilde{\phi}_0$. Then firm 0 sells the technology to firm 1 at stage S_1 if and only if

$$\pi^r_1 - \pi^n_1 \geq \pi^r_2 - \pi^x_2 + \lambda_{02}(\pi^x_2 - \pi^n_2), \tag{A.20}$$

which does not depend on λ_{01}. Given some λ_{02}, it only depends on the incremental profits of each firm due to technology transfer.

In each of the cases considered so far, we have seen that the common ownership incentive λ_{01} has either no or a positive effect on the likelihood that firm 1 becomes the assignee in equilibrium, conditional on observing technology transfer. However, it depends on λ_{01} which of the cases occurs, since $\tilde{\phi}_0$ is an increasing function of common ownership incentives. Therefore, we must consider what happens at the thresholds that discriminates the three cases.

Case 3 can occur if λ_{01} is sufficiently low. Increasing λ_{01} we see from (A.16) that we can cross a threshold $\hat{\lambda}_{01}$ at which we go from the third case (in which it is possible to sell to firm 2 at S_2 if $\lambda_{01} \leq \hat{\lambda}_{01}$) to the case 2 (in which firm 0 never will sell to firm 2 at stage S_2 if $\lambda_{01} > \hat{\lambda}_{01}$). In this case, the probability that firm 1 becomes the assignee increases in λ_{01}. By (A.16) this threshold is

$$\hat{\lambda}_{01} \equiv \frac{\pi_2^r - \tilde{\pi}_2 - C}{\tilde{\pi}_1 - \pi_1^n}, \tag{A.21}$$

i.e., the ratio of the benefit from selling to firm 2 at S_2 and firm 1's cost of being the outsider of this deal. Increasing λ_{01} further can lead eventually to case 1, in which firm 2 never becomes the assignee. Both thresholds coincide if firm 0 does not find it profitable to sell to firm 1 in state S_2. Thus, the relationship between λ_{01} and the probability that firm 1 is the assignee in equilibrium is weakly monotonous and increasing if either firm 1 is the assignee in all three cases (for all the respective λ_{01}), or firm 1 becomes the assignee for some $\lambda_{01} > \hat{\lambda}_{01}$ in cases 1 or 2, while in case 3 firm 2 is the assignee.

Since the left-hand side of (A.19) increases in λ_{01}, we have to check if for some λ_{01} larger but close to the threshold $\hat{\lambda}_{01}$ it is possible that (A.19) is violated while (A.20) holds. This would imply that for any $\lambda_{01} \leq \hat{\lambda}_{01}$ firm 0 sells the technology to firm 1, but for some higher $\lambda_{01} > \hat{\lambda}_{01}$ it sells to firm 2. Comparing the two inequalities for the two cases and using the definition of $\hat{\lambda}_{01}$, we see that this is only possible if

$$\tilde{\pi}_1 - \pi_1^n > \pi_2^r - \tilde{\pi}_2 - C, \quad \text{and} \tag{A.22}$$

$$\pi_1^r - \tilde{\pi}_1 - C < \lambda_{02}(\pi_2^x - \pi_2^n) + (\tilde{\pi}_2 - \pi_2^x). \tag{A.23}$$

Notice, that the two terms in brackets of the right-hand side of (A.23) are either equal to $(\tilde{\pi}_2 - \pi_2^n)$ or 0, as $\pi_2^x \in \{\pi_2^n, \tilde{\pi}_2\}$. On the one hand, inequality (A.22) tells us that the business stealing effect that hurts firm 1 is higher than the benefit that the technology transfer generates when firm 2 is the adopter. Therefore, firm 0 offers the technology to firm 1 at S_1 in case 3, since it can profit from a high fixed fee F_1 due to the threat to sell to firm 2 afterward if firm 1 rejects the offer. On the other hand, inequality (A.23) shows that in case 2, when firm 0 is never willing to sell the technology to firm 2 at stage S_2, the benefit from selling to firm 1 at S_2 must be small compared to the business stealing effect it has on firm 2. Therefore, in case 2, firm 0 sells to firm 2 at S_1 if (A.23) holds. If both inequalities are satisfied, an increase in λ_{01}, crossing the threshold $\hat{\lambda}_{01}$, leads to a negative relationship between λ_{01} around the threshold and the probability of selling to firm 1. However, a further increase of λ_{01} could reverse firm 0's decision, making it again more likely that firm 1 becomes the assignee because the left-hand side of (A.19) increases in λ_{01}.

For this special case to arise, we need that business stealing effects are larger than the social surplus of technology transfer, as indicated by (A.22) and (A.23). This does not seem very plausible in the case of patent trades. Furthermore, an arrangement of non-exclusive licensing contracts could be more profitable in this case. However, this is beyond the scope of this paper.

A.4 Proof of proposition 2

Proof. 1. It follows directly from (2.10) and

$$\frac{\partial}{\partial \lambda_{0l}}\left[\Delta_l + \lambda_{0l}\left(1-\frac{1}{2}\lambda_{0l}\right)\frac{\gamma^2}{\nu}\right] = (1-\lambda_{0l})\frac{\gamma^2}{\nu} > 0, \quad \text{for all } \lambda_{0l} < 1. \tag{A.24}$$

2. Rearranging $\Delta\pi_1 - \frac{1}{2}\nu k_1^2 \geq \Delta\pi_2 - \frac{1}{2}\nu k_2^2$ yields the inequality

$$\lambda_{01}^2 - 2\lambda_{01} + 2\frac{\nu}{\gamma^2}(\Delta_2 - \Delta_1) + 2\lambda_{02}\left(1-\frac{1}{2}\lambda_{02}\right) \leq 0.$$

Solving the corresponding quadratic equation yields two solutions, namely

$$\begin{aligned}\bar{\lambda}_{01} =& 1 - \sqrt{1 - 2\frac{\nu}{\gamma^2}(\Delta_2 - \Delta_1) - 2\lambda_{02}(1-\frac{1}{2}\lambda_{02})},\\ \bar{\lambda}'_{01} =& 1 + \sqrt{1 - 2\frac{\nu}{\gamma^2}(\Delta_2 - \Delta_1) - 2\lambda_{02}(1-\frac{1}{2}\lambda_{02})},\end{aligned}$$

and $\Delta\pi_1 - \frac{1}{2}\nu k_1^2 \geq \Delta\pi_2 - \frac{1}{2}\nu k_2^2$ holds if $\bar{\lambda}_{01} \leq \lambda_{01} \leq \bar{\lambda}'_{01}$. However, the profit from assigning the technology to firm 2, $\Delta\pi_2 - \frac{1}{2}\nu k_2^2$, increases and $\bar{\lambda}'_{01}$ decreases in Δ_2 and λ_{02}. This implies that the profit from assigning to firm 1 has to be decreasing in λ_{01} around the threshold $\bar{\lambda}'_{01}$. By (A.24), this implies that $\bar{\lambda}'_{01} > 1$. Thus, the relevant threshold is $\bar{\lambda}_{01}$. □

Appendix B

Automation and Sectoral Reallocation

B.1 Proof of Proposition 1

Proof. From the maximization problem of the household we have,

$$\Phi l_t^{-\varphi} = \lambda_t^{n^M} \psi_t^{hM} s_t + \lambda_t^{n^S} \psi_t^{hS} (1 - s_t) + \lambda_t^c \bar{b}_t, \tag{B.1}$$

and

$$\lambda_t^{n^M} \psi_t^{hM} = \lambda_t^{n^S} \psi_t^{hS}. \tag{B.2}$$

We can substitute (B.2) into (B.1) and obtain,

$$\Phi l_t^{-\varphi} = \lambda_t^{n^S} \psi_t^{hM} + \lambda_t^c \bar{b}_t,$$

or alternatively we can get,

$$\Phi l_t^{-\varphi} = \lambda_t^{n^S} \psi_t^{hS} + \lambda_t^c \bar{b}_t,$$

which states that the marginal utility of leisure is equal to the value of being unemployed. The latter in turn is equal to the utility value of the unemployment benefit plus the probability of finding a job times the value of being employed. We invert these equations and obtain,

$$\lambda_t^{n^M} = \frac{\Phi l_t^{-\varphi} - \lambda_t^c \bar{b}_t}{\psi_t^{hM}},$$

and

$$\lambda_t^{n^S} = \frac{\Phi l_t^{-\varphi} - \lambda_t^c \bar{b}_t}{\psi_t^{hS}}.$$

The values of an additional unit of employment in the two sectors are,

$$V_{n^M t}^h = \lambda_t^c w_t^M - \Phi l_t^{-\varphi} + \left(1 - \sigma^M\right) \lambda_t^{n^M},$$

and

$$V^h_{n^S t} = \lambda^c_t w^S_t - \varPhi l^{-\varphi}_t + \left(1 - \sigma^S\right) \lambda^{n^S}_t .$$

The Lagrange multipliers $\lambda^{n^M}_t$ and $\lambda^{n^S}_t$ are equal to,

$$\lambda^{n^M}_t = \beta E_t \left[\lambda^c_{t+1} w^M_{t+1} - \varPhi l^{-\varphi}_{t+1} + \lambda^{n^M}_{t+1}(1 - \sigma^M)\right],$$

and

$$\lambda^{n^S}_t = \beta E_t \left[\lambda^c_{t+1} w^S_{t+1} - \varPhi l^{-\varphi}_{t+1} + \lambda^{n^S}_{t+1}(1 - \sigma^S)\right].$$

Therefore, we can write,

$$\lambda^{n^S}_t = \beta E_t \left[V^h_{n^S t+1}\right], \tag{B.3}$$

and

$$\lambda^{n^M}_t = \beta E_t \left[V^h_{n^M t+1}\right]. \tag{B.4}$$

Consider now the problems of the two representative firms where the first-order conditions with respect to vacancies are given by,

$$\frac{\kappa^M}{\psi^{fM}_t} = E_t \varLambda_{t,t+1} \left[p^M_{t+1}(1 - \zeta) \left(\frac{M_{t+1}}{n^M_{t+1}}\right)^{\frac{1}{\alpha}} - w^M_{t+1} + \frac{\left(1 - \sigma^M\right) \kappa^M}{\psi^{fM}_{t+1}}\right],$$

and

$$\frac{\kappa^S}{\psi^{fS}_t} = E_t \varLambda_{t,t+1} \left[p^S_{t+1}(1 - \xi) \left(\frac{S_{t+1}}{n^S_{t+1}}\right)^{\frac{1}{\rho}} - w^S_{t+1} + \frac{\left(1 - \sigma^S\right) \kappa^S}{\psi^{fS}_{t+1}}\right].$$

The marginal value of an extra unit of employment in period t for each sector is,

$$V^f_{n^M t} = p^M_t (1 - \zeta) \left(\frac{M_t}{n^M_t}\right)^{\frac{1}{\alpha}} - w^M_t + \frac{\left(1 - \sigma^M\right) \kappa^M}{\psi^{fM}_t},$$

and

$$V^f_{n^S t} = p^S_t (1 - \xi) \left(\frac{S_t}{n^S_t}\right)^{\frac{1}{\rho}} - w^S_t + \frac{\left(1 - \sigma^S\right) \kappa^S}{\psi^{fS}_t}.$$

Therefore, we can write,

$$\frac{\kappa^M}{\psi^{fM}_t} = E_t \varLambda_{t,t+1} \left[V^f_{n^M t+1}\right], \tag{B.5}$$

and

$$\frac{\kappa^S}{\psi^{fS}_t} = E_t \varLambda_{t,t+1} \left[V^f_{n^S t+1}\right].$$

Recall that the first-order conditions of the wage bargaining problems are,

$$\vartheta^M V^h_{n^M t} = \left(1-\vartheta^M\right)\lambda^c_t V^f_{n^M t}, \tag{B.6}$$

and

$$\vartheta^S V^h_{n^S t} = \left(1-\vartheta^S\right)\lambda^c_t V^f_{n^S t}.$$

By evaluating equation (B.6) for the next period, multiplying by $\frac{\beta}{\lambda^c_t}$, and taking expectations we obtain,

$$\frac{\vartheta^M}{\lambda^c_t}\beta E_t\left[V^h_{n^M t+1}\right] = \left(1-\vartheta^M\right)E_t\Lambda_{t,t+1}\left[V^f_{n^M t+1}\right].$$

Substituting (B.4) and (B.5) we get,

$$\frac{\vartheta^M}{\lambda^c_t}\frac{\left(\Phi l_t^{-\varphi}-\lambda^c_t\bar{b}_t\right)}{\psi^{hM}_t} = \left(1-\vartheta^M\right)\frac{\kappa^M}{\psi^{fM}_t},$$

and, after rearranging terms, we obtain,

$$\theta^M_t = \frac{\vartheta^M}{1-\vartheta^M}\frac{\left(\Phi l_t^{-\varphi}-\lambda^c_t\bar{b}_t\right)}{\kappa^M}.$$

Similarly for the service sector, we have,

$$\theta^S_t = \frac{\vartheta^S}{1-\vartheta^S}\frac{\left(\Phi l_t^{-\varphi}-\lambda^c_t\bar{b}_t\right)}{\kappa^S}.$$

These relations are similar to the the linear relationship between labor market tightness and the marginal utility of consumption derived by Ravn (2008) in a one-sector search and matching model with endogenous participation. By taking the ratio of tightness in the two sectors and considering the steady-state equilibrium, we obtain the relationship of Proposition 1.

$$\frac{\theta^M}{\theta^S} = \frac{\frac{\vartheta^M}{1-\vartheta^M}}{\frac{\vartheta_S}{1-\vartheta_S}}\cdot\frac{\kappa^S}{\kappa^M}.$$

□

B.2 The maximization problem of the household

The Lagrangian is given by:

$$\begin{aligned}\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ & \frac{c_t^{1-\eta}}{1-\eta} + \Phi \frac{\left[1 - u_t - n_t^M - n_t^S\right]^{1-\varphi}}{1-\varphi} \\ & - \lambda_t^c \left[c_t + k_{t+1} - (1-\delta)k_t - r_t k_t - w_t^M n_t^M - w_t^S n_t^S - \bar{b}_t u_t - \Pi_t^M - \Pi_t^S\right] \\ & - \lambda_t^{n^M} \left[n_{t+1}^M - \left(1 - \sigma^M\right) n_t^M - \psi_t^{hM} s_t u_t\right] \\ & - \lambda_t^{n^S} \left[n_{t+1}^S - \left(1 - \sigma^S\right) n_t^S - \psi_t^{hS} (1 - s_t) u_t\right] \Bigg\}.\end{aligned}$$

The first-order conditions with respect to c_t, k_{t+1}, n_{t+1}^M, n_{t+1}^S, u_t, and s_t are,
[wrt c_t]

$$c_t^{-\eta} - \lambda_t^c = 0, \tag{B.7}$$

[wrt k_{t+1}]

$$-\beta^t \lambda_t^c + \beta^{t+1} E_t \left[\lambda_{t+1}^c (1 - \delta + r_{t+1})\right] = 0, \tag{B.8}$$

[wrt n_{t+1}^M]

$$-\beta^t \lambda_t^{n^M} + \beta^{t+1} E_t \left[-\Phi l_{t+1}^{-\varphi} + \lambda_{t+1}^c w_{t+1}^M + \lambda_{t+1}^{n^M} (1 - \sigma^M)\right] = 0, \tag{B.9}$$

[wrt n_{t+1}^S]

$$-\beta^t \lambda_t^{n^S} + \beta^{t+1} E_t \left[-\Phi l_{t+1}^{-\varphi} + \lambda_{t+1}^c w_{t+1}^S + \lambda_{t+1}^{n^S} (1 - \sigma^S)\right] = 0, \tag{B.10}$$

[wrt u_t]

$$-\beta^t \Phi l_t^{-\varphi} + \beta^t \lambda_t^c \bar{b}_t + \beta^t \lambda_t^{n^M} \psi_t^{hM} s_t + \beta^t \lambda_t^{n^S} \psi_t^{hS} (1 - s_t) = 0, \tag{B.11}$$

[wrt s_t]

$$\lambda_t^{n^M} \psi_t^{hM} - \lambda_t^{n^S} \psi_t^{hS} = 0. \tag{B.12}$$

To simplify the system of equations, we combine (B.7) and (B.8),

$$c_t^{-\eta} = \beta E_t \left[c_{t+1}^{-\eta} (1 - \delta + r_{t+1})\right], \tag{B.13}$$

and then rearrange terms in (B.9) - (B.12),

$$\lambda_t^{n^M} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^M + \lambda_{t+1}^{n^M} (1 - \sigma^M)\right], \tag{B.14}$$

$$\lambda_t^{n^S} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^S + \lambda_{t+1}^{n^S} (1 - \sigma^S)\right], \tag{B.15}$$

$$\Phi l_t^{-\varphi} = \lambda_t^{n^M} \psi_t^{hM} s_t + \lambda_t^{n^S} \psi_t^{hS} (1 - s_t) + \lambda_t^c \bar{b}_t, \tag{B.16}$$

$$\lambda_t^{n^M} \psi_t^{hM} = \lambda_t^{n^S} \psi_t^{hS}. \tag{B.17}$$

B.3 The wage bargaining problem

B.3.1 Manufacturing sector

The maximization problem is written as,

$$\max_{w_t^M} \left\{ \left(1-\vartheta^M\right) \ln V^h_{n^M t} + \vartheta^M \ln V^f_{n^M t} \right\}, \tag{B.18}$$

where

$$V^h_{n^M_t} = -\Phi l_t^{-\varphi} + \lambda_t^c w_t^M + (1-\sigma^M)\lambda_t^{n^M}, \tag{B.19}$$

and

$$V^f_{n^M t} = p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} - w_t^M + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}}. \tag{B.20}$$

The first-order condition is written as,

$$\vartheta^M V^h_{n^M t} = \left(1-\vartheta^M\right) \lambda_t^c V^f_{n^M t}.$$

Using (B.19) and (B.20), we obtain,

$$\vartheta^M \left(\lambda_t^c w_t^M - \Phi l_t^{-\varphi} + (1-\sigma^M)\lambda_t^{n^M}\right) = \\ \left(1-\vartheta^M\right) \lambda_t^c \left(p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} - w_t^M + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}} \right),$$

$$\vartheta^M \lambda_t^c w_t^M + \vartheta^M \left(-\Phi l_t^{-\varphi} + (1-\sigma^M)\lambda_t^{n^M}\right) = \\ -(1-\vartheta^M)\lambda_t^c w_t^M + \left(1-\vartheta^M\right) \lambda_t^c \left(p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}} \right),$$

$$\vartheta^M \lambda_t^c w_t^M + (1-\vartheta^M)\lambda_t^c w_t^M = \\ -\vartheta^M \left(-\Phi l_t^{-\varphi} + (1-\sigma^M)\lambda_t^{n^M}\right) + \left(1-\vartheta^M\right) \lambda_t^c \left(p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}} \right).$$

The final expression for the wage in the manufacturing sector is,

$$w_t^M = \left(1-\vartheta^M\right) \left(p_t^M (1-\zeta) \left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}} \right) - \frac{\vartheta^M}{\lambda_t^c} \left((1-\sigma^M)\lambda_t^{n^M} - \Phi l_t^{-\varphi}\right).$$

B.3.2 Service sector

Similarly, the maximization problem is written as,

$$\max_{w_t^S}\left\{\left(1-\vartheta^S\right)\ln V^h_{n^S t}+\vartheta^S\ln V^f_{n^S t}\right\}, \tag{B.21}$$

where

$$V^h_{n^S t}=\lambda_t^c w_t^S-\Phi l_t^{-\varphi}+\left(1-\sigma^S\right)\lambda_t^{n^S}, \tag{B.22}$$

and

$$V^f_{n^S t}=p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}-w_t^S+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}. \tag{B.23}$$

The first-order condition is written as,

$$\vartheta^S V^h_{n^S t}=\left(1-\vartheta^S\right)\lambda_t^c V^f_{n^S t}.$$

Using (B.22) and (B.23) we obtain,

$$\vartheta^S(\lambda_t^c w_t^S-\Phi l_t^{-\varphi}+\left(1-\sigma^S\right)\lambda_t^{n^S})=\left(1-\vartheta^S\right)\lambda_t^c(p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}-w_t^S+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}).$$

We perform a simple algebra below,

$$\begin{aligned}&\vartheta^S\lambda_t^c w_t^S+\vartheta^S(-\Phi l_t^{-\varphi}+\left(1-\sigma^S\right)\lambda_t^{n^S})=\\&\qquad-\left(1-\vartheta^S\right)\lambda_t^c w_t^S+\left(1-\vartheta^S\right)\lambda_t^c(p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}),\end{aligned}$$

or equivalently,

$$\begin{aligned}&\vartheta^S\lambda_t^c w_t^S+\left(1-\vartheta^S\right)\lambda_t^c w_t^S=\\&\qquad\left(1-\vartheta^S\right)\lambda_t^c(p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}})-\vartheta^S(-\Phi l_t^{-\varphi}+\left(1-\sigma^S\right)\lambda_t^{n^S}),\end{aligned}$$

or equivalently,

$$w_t^S\lambda_t^c=\left(1-\vartheta^S\right)\lambda_t^c(p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}})-\vartheta^S(-\Phi l_t^{-\varphi}+\left(1-\sigma^S\right)\lambda_t^{n^S}).$$

The final expression for the equilibrium wage is given by,

$$w_t^S=\left(1-\vartheta^S\right)\left(p_t^S(1-\xi)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}}+\frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}\right)-\frac{\vartheta^S}{\lambda_t^c}((\left(1-\sigma^S\right)\lambda_t^{n^S}-\Phi l_t^{-\varphi}).$$

B.4 Resource constraint

From the household budget constraint,

$$c_t + i_t = r_t k_t + w_t^M n_t^M + w_t^S n_t^S + \bar{b}_t u_t - T_t + \Pi_t^M + \Pi_t^S.$$

We substitute the expressions of the instantaneous profits of firms,

$$\Pi_t^M = p_t^M M_t - w_t^M n_t^M - r_t k_t^M - \kappa^M v_t^M,$$

$$\Pi_t^S = p_t^S S_t - w_t^S n_t^S - r_t k_t^S - \kappa^S v_t^S,$$

and obtain,

$$c_t + i_t = p_t^M M_t + p_t^S S_t - \kappa^S v_t^S - \kappa^M v_t^m.$$

Because of the constant returns to scale and frictionless production of the final good, we have,

$$Y_t = p_t^M M_t + p_t^S S_t.$$

So, we obtain the resource constraint,

$$Y_t = c_t + i_t + \kappa^S v_t^S + \kappa^M v_t^m.$$

B.5 Model Solution

We report below all equations that need to be satisfied in equilibrium.

Labor markets

$$m_t^M = \mu_1 (v_t^M)^{\mu_2} (u_t^M)^{1-\mu_2} \tag{E.1}$$

$$m_t^S = \mu_1 (v_t^S)^{\mu_2} (u_t^S)^{1-\mu_2} \tag{E.2}$$

$$n_{t+1}^M = (1 - \sigma^M) n_t^M + m_t^M \tag{E.3}$$

$$n_{t+1}^S = (1 - \sigma^S) n_t^S + m_t^S \tag{E.4}$$

$$\psi_t^{hM} \equiv \frac{m_t^M}{u_t^M} \tag{E.5}$$

$$\psi_t^{fM} \equiv \frac{m_t^M}{v_t^M} \tag{E.6}$$

$$\psi_t^{hS} \equiv \frac{m_t^S}{u_t^S} \tag{E.7}$$

$$\psi_t^{fS} \equiv \frac{m_t^S}{\upsilon_t^S} \tag{E.8}$$

Household

$$c_t^{-\eta} = \beta E_t \left[c_{t+1}^{-\eta}(1 - \delta + r_{t+1}) \right] \tag{E.9}$$

$$\lambda_t^{n^M} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^M + \lambda_{t+1}^{n^M}(1 - \sigma^M) \right] \tag{E.10}$$

$$\lambda_t^{n^S} = \beta E_t \left[-\Phi l_{t+1}^{-\varphi} + c_{t+1}^{-\eta} w_{t+1}^S + \lambda_{t+1}^{n^S}(1 - \sigma^S) \right] \tag{E.11}$$

$$\Phi l_t^{-\varphi} = \lambda_t^{n^M} \psi_t^{hM} s_t + \lambda_t^{n^S} \psi_t^{hS}(1 - s_t) + \lambda_t^c \bar{b}_t \tag{E.12}$$

$$\lambda_t^{n^M} \psi_t^{hM} = \lambda_t^{n^S} \psi_t^{hS} \tag{E.13}$$

$$n_t^M + n_t^S + u_t + l_t = 1 \tag{E.14}$$

$$u_t^M = s_t u_t \tag{E.15}$$

$$u_t^S = (1 - s_t) u_t \tag{E.16}$$

$$c_t + k_{t+1} = (1 - \delta + r_t) k_t + w_t^M n_t^M + w_t^S n_t^S + \bar{b}_t u_t - T_t + \Pi_t^M + \Pi_t^S \tag{E.17}$$

Capital market clearing

$$k_t = k_t^M + k_t^S \tag{E.18}$$

Firms

$$\Lambda_{t,t+1} = \beta \left(\frac{\lambda_{t+1}^c}{\lambda_t^c} \right) \tag{E.19}$$

$$\frac{\kappa^M}{\psi_t^{fM}} = E_t \Lambda_{t,t+1} \left[p_{t+1}^M (1 - \zeta) \left(\frac{M_{t+1}}{n_{t+1}^M} \right)^{\frac{1}{\alpha}} - w_{t+1}^M + \frac{\left(1 - \sigma^M\right) \kappa^M}{\psi_{t+1}^{fM}} \right] \tag{E.20}$$

$$r_t = p_t^M \cdot \zeta \left(\frac{M_t}{k_t^M}\right)^{\frac{1}{\alpha}} \tag{E.21}$$

$$p_t^M = \gamma \left(\frac{Y_t}{M_t}\right)^{\frac{1}{\chi}} \tag{E.22}$$

$$M_t = \left[\zeta(k_t^M)^{\frac{\alpha-1}{\alpha}} + (1-\zeta)(n_t^M)^{\frac{\alpha-1}{\alpha}}\right]^{\frac{\alpha}{\alpha-1}} \tag{E.23}$$

$$Y_t = \left[\gamma M_t^{\frac{\chi-1}{\chi}} + (1-\gamma)S_t^{\frac{\chi-1}{\chi}}\right]^{\frac{\chi}{\chi-1}} \tag{E.24}$$

$$\frac{\kappa^S}{\psi_t^{fS}} = E_t \Lambda_{t,t+1}\left[p_{t+1}^S\left(1-\xi\right)\left(\frac{S_{t+1}}{n_{t+1}^S}\right)^{\frac{1}{\rho}} - w_{t+1}^S + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi_{t+1}^{fS}}\right] \tag{E.25}$$

$$r_t = p_t^S \cdot \xi \left(\frac{S_t}{k_t^S}\right)^{\frac{1}{\rho}} \tag{E.26}$$

$$p_t^S = (1-\gamma)\left(\frac{Y_t}{S_t}\right)^{\frac{1}{\chi}} \tag{E.27}$$

$$S_t = \left[\xi(k_t^S)^{\frac{\rho-1}{\rho}} + (1-\xi)(n_t^S)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{E.28}$$

Wages

$$w_t^S = \left(1-\vartheta^S\right)\left(p_t^S\left(1-\xi\right)\left(\frac{S_t}{n_t^S}\right)^{\frac{1}{\rho}} + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi_t^{fS}}\right) + \frac{\vartheta^S}{\lambda_t^c}(\Phi l_t^{-\varphi} - \left(1-\sigma^S\right)\lambda_t^{n^S}) \tag{E.29}$$

$$w_t^M = \left(1-\vartheta^M\right)\left(p_t^M(1-\zeta)\left(\frac{M_t}{n_t^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi_t^{fM}}\right) + \frac{\vartheta^M}{\lambda_t^c}(\Phi l_t^{-\varphi} - \left(1-\sigma^M\right)\lambda_t^{n^M}) \tag{E.30}$$

B.6 Steady-state system of equations

$$m^M = \mu_1 (\upsilon^M)^{\mu_2} (u^M)^{1-\mu_2} \tag{S.1}$$

$$m^S = \mu_1 (\upsilon^S)^{\mu_2} (u^S)^{1-\mu_2} \tag{S.2}$$

$$n^M = \frac{m^M}{\sigma^M} \tag{S.3}$$

$$n^S = \frac{m^S}{\sigma^S} \tag{S.4}$$

$$\psi^{hM} \equiv \frac{m^M}{u^M}, \tag{S.5}$$

$$\psi^{fM} \equiv \frac{m^M}{\upsilon^M}, \tag{S.6}$$

$$\psi^{hS} \equiv \frac{m^S}{u^S}, \tag{S.7}$$

$$\psi^{fS} \equiv \frac{m^S}{\upsilon^S} \tag{S.8}$$

Household

$$r = \frac{1-\beta}{\beta} + \delta \tag{S.9}$$

$$\lambda^{n^M} = \beta \left[-\mathit{\Phi} l^{-\varphi} + c^{-\eta} w^M + \lambda^{n^M} (1 - \sigma^M) \right] \tag{S.10}$$

$$\lambda^{n^S} = \beta \left[-\mathit{\Phi} l^{-\varphi} + c^{-\eta} w^S + \lambda^{n^S} (1 - \sigma^S) \right] \tag{S.11}$$

$$\mathit{\Phi} l^{-\varphi} = \lambda^{n^M} \psi^{hM} s + \lambda^{n^S} \psi^{hS} (1-s) + \lambda^c \bar{b} \tag{S.12}$$

$$\lambda^{n^M} \psi^{hM} = \lambda^{n^S} \psi^{hS} \tag{S.13}$$

$$n^M + n^S + u + l = 1 \tag{S.14}$$

$$u^M = su \tag{S.15}$$

$$u^S = (1-s)u \tag{S.16}$$

$$c = k(r-\delta) + w^M n^M + w^S n^S + \bar{b}u \tag{S.17}$$

Capital market clearing

$$k = k^M + k^S \tag{S.18}$$

Firms

$$\frac{\kappa^S}{\psi^{fS}} = \beta\left[p^S\left(1-\xi\right)\left(\frac{S}{n^S}\right)^{\frac{1}{\rho}} - w^S + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi^{fS}}\right] \tag{S.19}$$

$$p^S = (1-\gamma)\left(\frac{Y}{S}\right)^{\frac{1}{\chi}} \tag{S.20}$$

$$S = \left[\xi(k^S)^{\frac{\rho-1}{\rho}} + (1-\xi)(n^S)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{S.21}$$

$$r = p^S \cdot \xi\left(\frac{S}{k^S}\right)^{\frac{1}{\rho}} \tag{S.22}$$

$$\frac{\kappa^M}{\psi_t^{fM}} = \beta\left[p^M(1-\zeta)\left(\frac{M}{n^M}\right)^{\frac{1}{\alpha}} - w^M + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi^{fM}}\right] \tag{S.23}$$

$$r = p^M \cdot \zeta\left(\frac{M}{k^M}\right)^{\frac{1}{\alpha}} \tag{S.24}$$

$$p^M = \gamma\left(\frac{Y}{M}\right)^{\frac{1}{\chi}} \tag{S.25}$$

$$M = \left[\zeta(k^M)^{\frac{\alpha-1}{\alpha}} + (1-\zeta)(n^M)^{\frac{\alpha-1}{\alpha}}\right]^{\frac{\alpha}{\alpha-1}} \tag{S.26}$$

Wages

$$w^S = \left(1-\vartheta^S\right)\left(p^S\left(1-\xi\right)\left(\frac{S}{n^S}\right)^{\frac{1}{\rho}} + + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi^{fS}}\right) + \frac{\vartheta^S}{\lambda^c}\left(\Phi l^{-\varphi} - \left(1-\sigma^S\right)\lambda^{n^S}\right) \tag{S.27}$$

$$w^M = \left(1-\vartheta^M\right)\left(p^M(1-\zeta)\left(\frac{M}{n^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi^{fM}}\right) + \frac{\vartheta^M}{\lambda^c}(\Phi l^{-\varphi} - \left(1-\sigma^M\right)\lambda^{n^M}) \tag{S.28}$$

B.6.1 Steady state - simplified system

Given the unknowns u, v^M, v^S, k^S, k^M, s, the following variables are determined sequentially:

$$r = \frac{1-\beta}{\beta} + \delta \tag{SS.1}$$

$$u^M = su \tag{SS.2}$$

$$u^S = (1-s)u \tag{SS.3}$$

$$m^M = \mu_1(\upsilon^M)^{\mu_2}(u^M)^{1-\mu_2} \tag{SS.4}$$

$$m^S = \mu_1(\upsilon^S)^{\mu_2}(u^S)^{1-\mu_2} \tag{SS.5}$$

$$n^M = \frac{m^M}{\sigma^M} \tag{SS.6}$$

$$n^S = \frac{m^S}{\sigma^S} \tag{SS.7}$$

$$\psi^{hM} \equiv \frac{m^M}{u^M}, \tag{SS.8}$$

$$\psi^{fM} \equiv \frac{m^M}{\upsilon^M}, \tag{SS.9}$$

$$\psi^{hS} \equiv \frac{m^S}{u^S}, \tag{SS.10}$$

$$\psi^{fS} \equiv \frac{m^S}{\upsilon^S} \tag{SS.11}$$

$$l = 1 - u - n^M - n^S \tag{SS.12}$$

$$S = \left[\xi(k^S)^{\frac{\rho-1}{\rho}} + (1-\xi)(n^S)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{SS.13}$$

$$M = \left[\zeta(k^M)^{\frac{\alpha-1}{\alpha}} + (1-\zeta)(n^M)^{\frac{\alpha-1}{\alpha}}\right]^{\frac{\alpha}{\alpha-1}} \tag{SS.14}$$

$$Y = \left[\gamma M^{\frac{\chi-1}{\chi}} + (1-\gamma)S^{\frac{\chi-1}{\chi}}\right]^{\frac{\chi}{\chi-1}} \tag{SS.15}$$

$$p^S = (1-\gamma)\left(\frac{Y}{S}\right)^{\frac{1}{\chi}} \tag{SS.16}$$

$$p^M = \gamma\left(\frac{Y}{M}\right)^{\frac{1}{\chi}} \tag{SS.17}$$

The wages of two sectors are obtained from the inverted FOCs with respect to sectoral employment:

$$w^S = p^S(1-\xi)\left(\frac{S}{n^S}\right)^{\frac{1}{\rho}} - \frac{\kappa^S}{\psi f^S \beta} + \frac{(1-\sigma^S)\kappa^S}{\psi f^S} \tag{SS.18}$$

$$w^M = p^M(1-\zeta)\left(\frac{M}{n^M}\right)^{\frac{1}{\alpha}} - \frac{\kappa^M}{\psi f^M \beta} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi f^M} \tag{SS.19}$$

$$\bar{b} = \varpi\frac{(w^m n^M + w^S n^S)}{n^M + n^S} \tag{SS.20}$$

$$T = \bar{b}u \tag{SS.21}$$

$$k = k^M + k^S \tag{SS.22}$$

$$c = k(r-\delta) + w^M n^M + w^S n^S + \bar{b}u - T + \Pi^M + \Pi^S \tag{SS.23}$$

$$\lambda^c = c^{-\eta} \tag{SS.24}$$

$$\lambda^{n^M} = \frac{\beta}{1-\beta(1-\sigma)}\left(c^{-\eta}w^M - \Phi l^{-\varphi}\right) \tag{SS.25}$$

$$\lambda^{n^S} = \frac{\beta}{1-\beta(1-\sigma)}\left(c^{-\eta}w^S - \Phi l^{-\varphi}\right) \tag{SS.26}$$

To solve for the unknowns, we numerically find the solution to the following system of equations, in which we use expressions (S.1) to (S.25).

$$\varPhi l^{-\varphi} = \lambda^{n^M}\psi^{hM}s + \lambda^{n^S}\psi^{hS}(1-s) + \lambda^c\bar{b} \tag{SS.27}$$

$$p^M \cdot \zeta \left(\frac{M}{k^M}\right)^{\frac{1}{\alpha}} - r = 0 \tag{SS.28}$$

$$p^S \cdot \xi \left(\frac{S}{k^S}\right)^{\frac{1}{\rho}} - r = 0 \tag{SS.29}$$

$$\frac{\kappa^S}{\psi^{fS}} = \beta\left[p^S(1-\xi)\left(\frac{S}{n^S}\right)^{\frac{1}{\rho}} - w^S + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi^{fS}}\right] \tag{SS.30}$$

$$\frac{\kappa^M}{\psi_t^{fM}} = \beta\left[p^M(1-\zeta)\left(\frac{M}{n^M}\right)^{\frac{1}{\alpha}} - w^M + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi^{fM}}\right] \tag{SS.31}$$

$$w^S = \left(1-\vartheta^S\right)\left(p^S(1-\xi)\left(\frac{S}{n^S}\right)^{\frac{1}{\rho}} + \frac{\left(1-\sigma^S\right)\kappa^S}{\psi^{fS}}\right) + \frac{\vartheta^S}{\lambda^c}(\varPhi l^{-\varphi} - \left(1-\sigma^S\right)\lambda^{n^S}) \tag{SS.32}$$

$$w^M = \left(1-\vartheta^M\right)\left(p^M(1-\zeta)\left(\frac{M}{n^M}\right)^{\frac{1}{\alpha}} + \frac{\left(1-\sigma^M\right)\kappa^M}{\psi^{fM}}\right) + \frac{\vartheta^M}{\lambda^c}(\varPhi l^{-\varphi} - \left(1-\sigma^M\right)\lambda^{n^M}) \tag{SS.33}$$

$$\lambda^{n^M}\psi^{hM} = \lambda^{n^S}\psi^{hS} \tag{SS.34}$$

B.7 Additional Figures

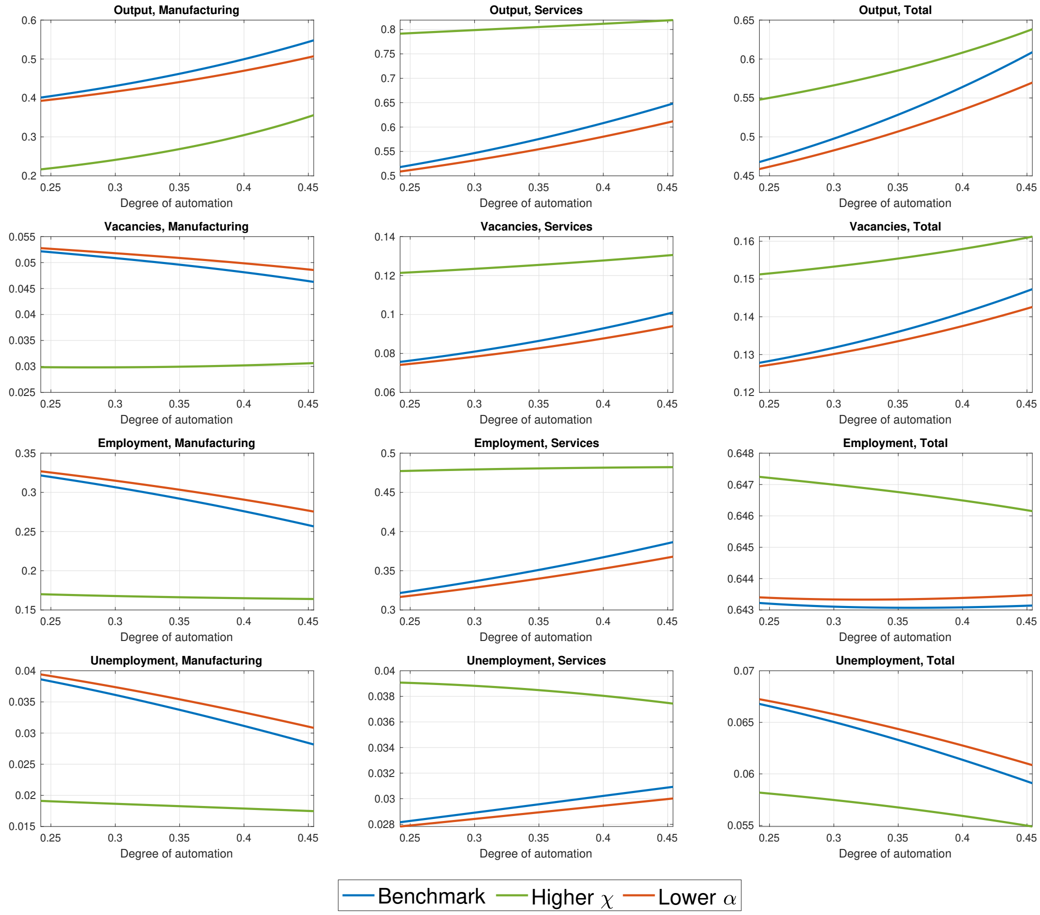

Figure B.1: Steady-state effects of automation in a two-sector economy: Different elasticities of substitution between capital and labor ($\alpha = 0.7$) and between the two goods ($\chi = 1.5$)

Note: The y-axis shows steady-state levels.

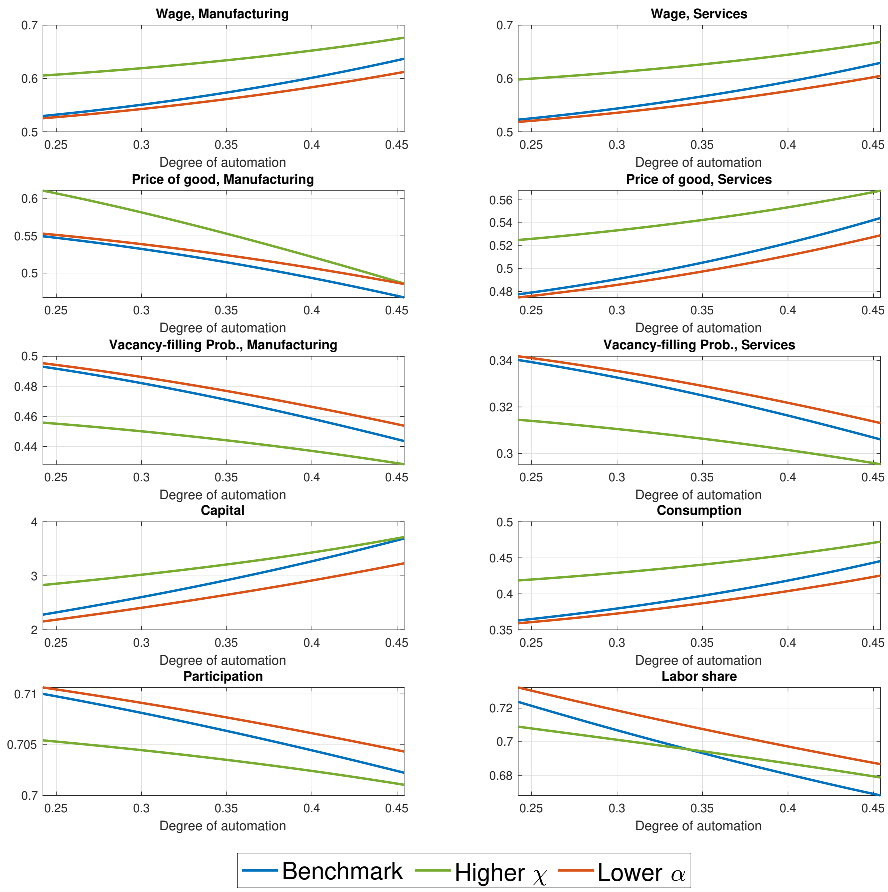

Figure B.2: Steady-state effects of automation in a two-sector economy: Different elasticities of substitution between capital and labor ($\alpha = 0.7$) and between the two goods ($\chi = 1.5$) (continued)

Note: The y-axis shows steady-state levels.

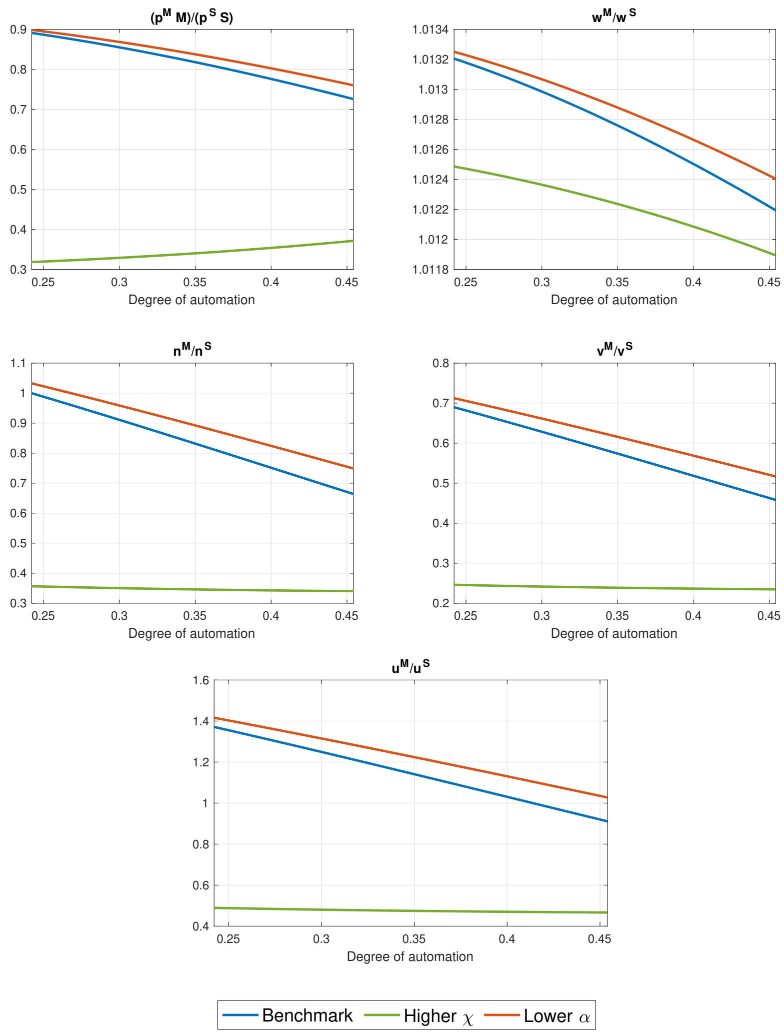

Figure B.3: Steady-state effects of automation on key ratios in a two-sector economy: Different elasticities of substitution between capital and labor ($\alpha = 0.7$) and between the two goods ($\chi = 1.5$)

Note: The y-axis shows steady-state levels.

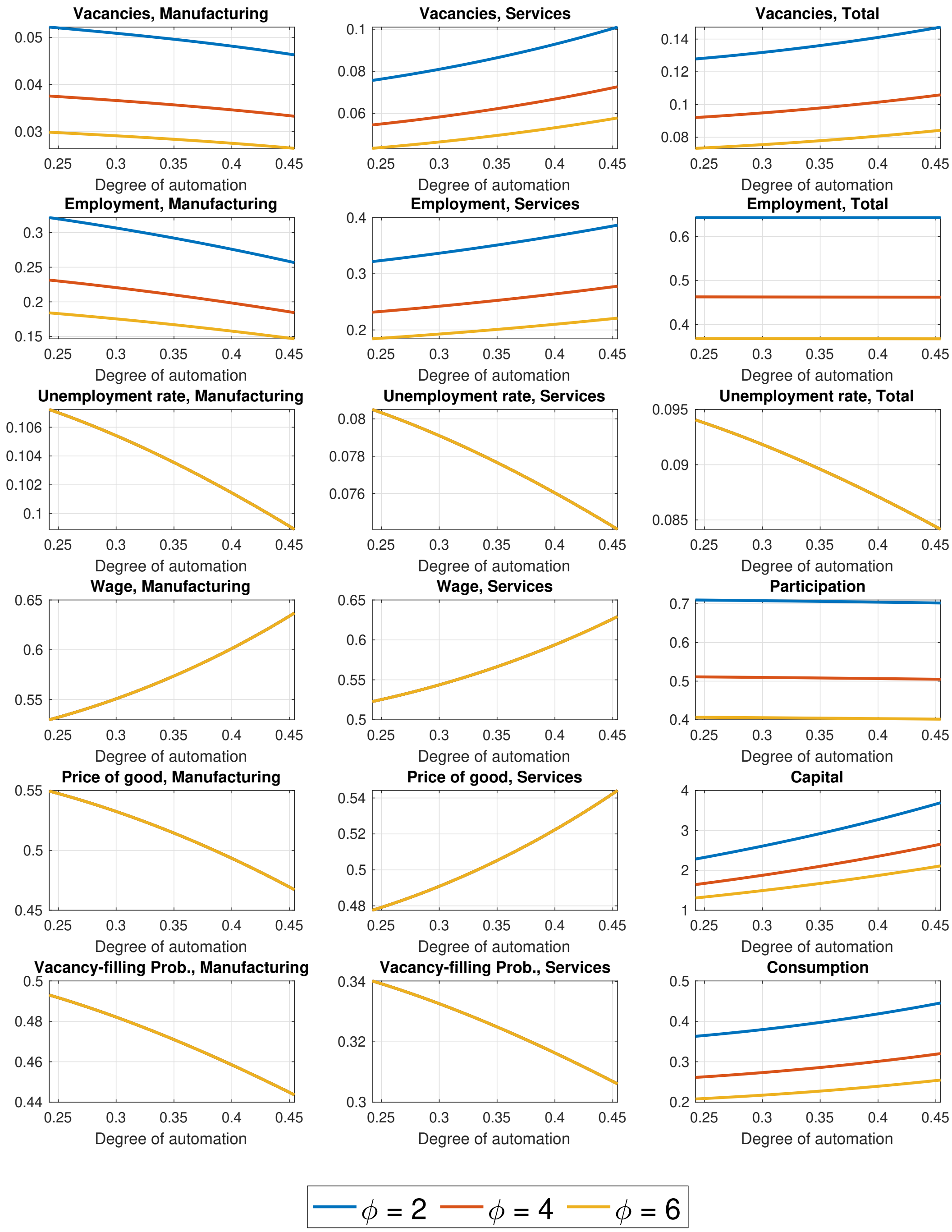

Figure B.4: Steady-state effects of automation in a two-sector economy: Different values of the Frisch elasticity

Note: The y-axis shows steady-state levels.

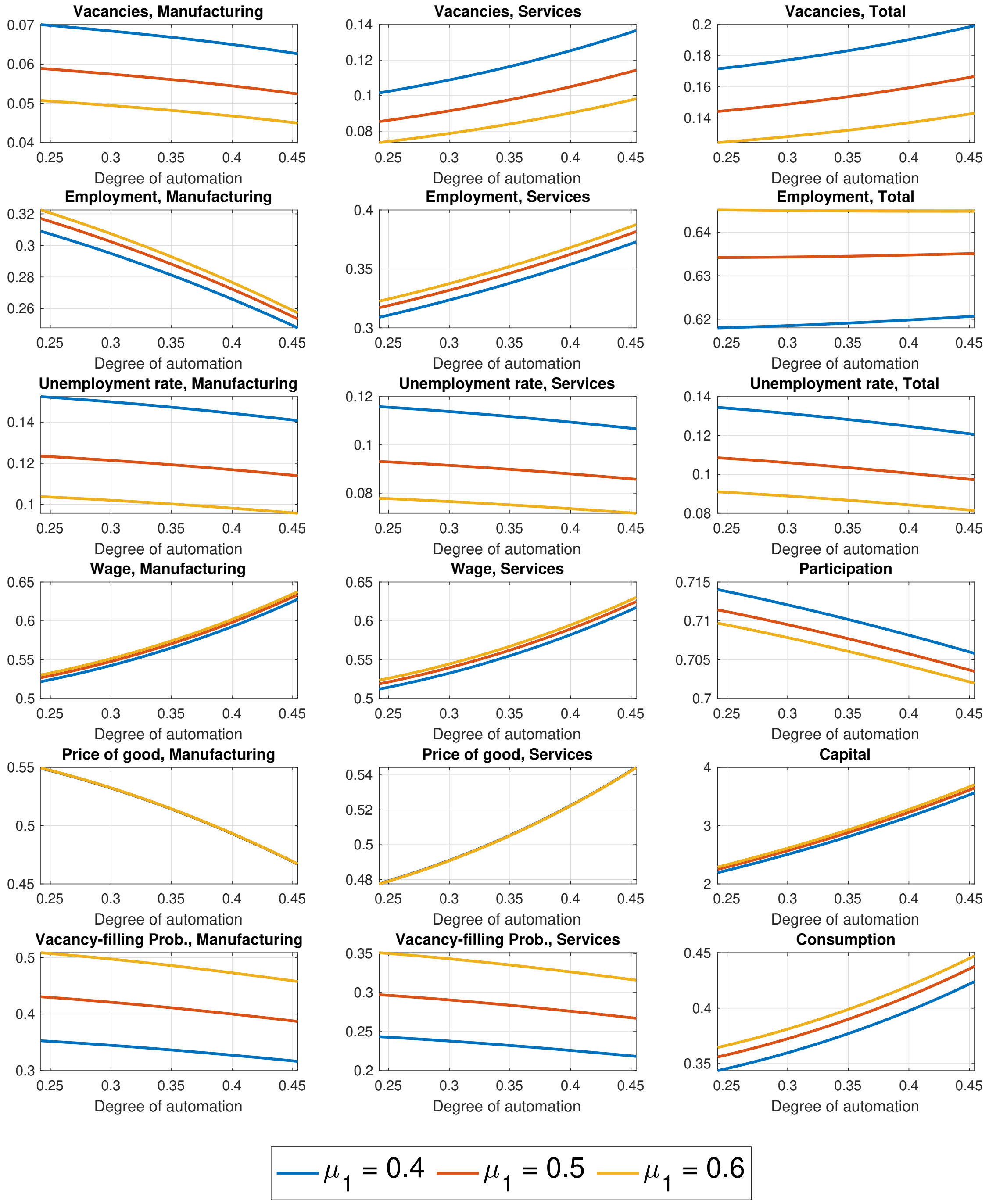

Figure B.5: Steady-state effects of automation in a two-sector economy: Different values of matching efficiency

Note: The y-axis shows steady-state levels.

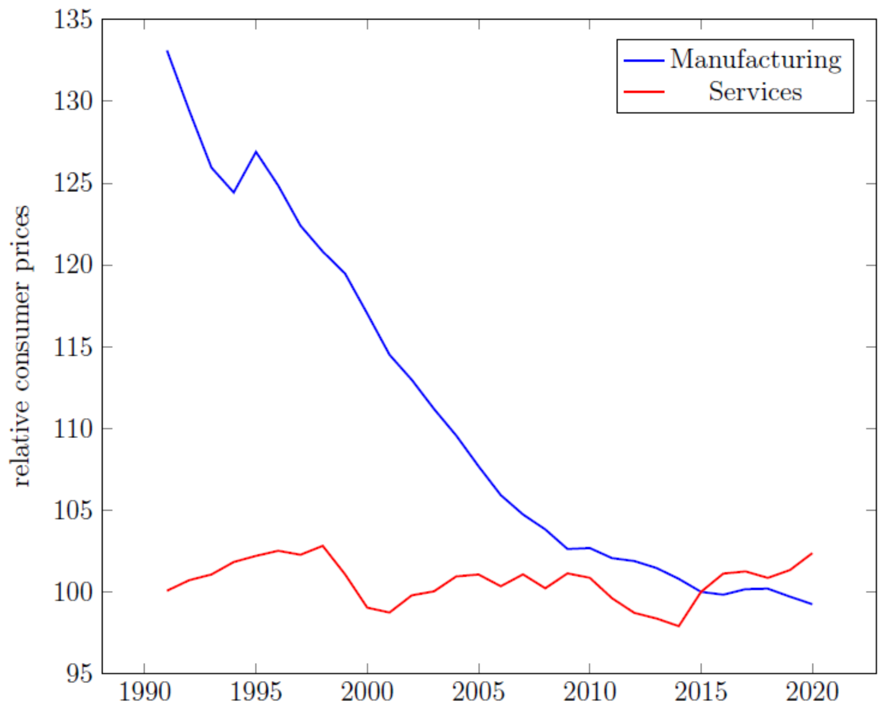

Figure B.6: Price Indexes for Manufacturing and Service goods normalized by the aggregate CPI (2015=100)

Note: We calculate the relative prices using the consumption basket weights and price indexes for goods and services from the Federal Statistical Office (Destatis) to match the definitions of the two sectors used throughout the paper. We normalize the indexes by the aggregate CPI (2015=100) representing the price of the numéraire good.