Ivory Power?

University regulations, knowledge transfers, and firm innovation

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This paper uncovers the short-term effect of academic knowledge transfers on a firm's innovation inputs and outputs. Not only do academic knowledge transfers require the intent of the university to send knowledge, they also require the intent of the firm to seek that knowledge in the first place. This makes transfers a highly endogenous variable shaped by a firm's strategic choices. This selection into treatment is governed by a firm's latent innovation ability biasing my regression estimates if I fail to fully control for those confounders. I use two ways to combat this confounding. First, I use panel data with two-way fixed effects for time and firm and control for a comprehensive set of start-of-period firm-level variables that covers most factors that shape firm choices but fail to cover for temporal changes in latent innovation abilities that arise among other things due to changes in the firm's staff. Second, I use a shift-share instrument that exploits quasi-random variation from changes to universities' laws and regulations of intellectual property rights. I show that these university-pushed supply shocks of academic knowledge were beyond the control of firms and hence act as an exogenous shock to them via their idiosyncratic exposures. I use Swiss firm-level survey data that spans from 1999 to 2018 and covers 4293 firms. I augment this data with university-level administrative data to construct the shocks, the instrument, and to conduct falsification tests on random shock assignment. The results show that academic knowledge transfers raise a firm's innovation input and output within the next 3 years where the effect on the former is larger. On the input side, transfers raise the propensity to spend on internal R&D by 14 percentage points (pp) and the internal R&D expenses by 16%. On the output side, they raise the propensity to develop a novel or improved product by 8 pp and the sales from novel or improved products by 7%. While the extensive margin effects are statistically significant at a 5 ‰ level, I fail to reject the absence of an effect for the intensive margin even at a 19% level. Overall, this study shows that academic knowledge is not only relevant via untargeted spillovers but also highly useful once targeted even in the short run.

JEL: I23, I28, O31, O34, O38

1 Introduction

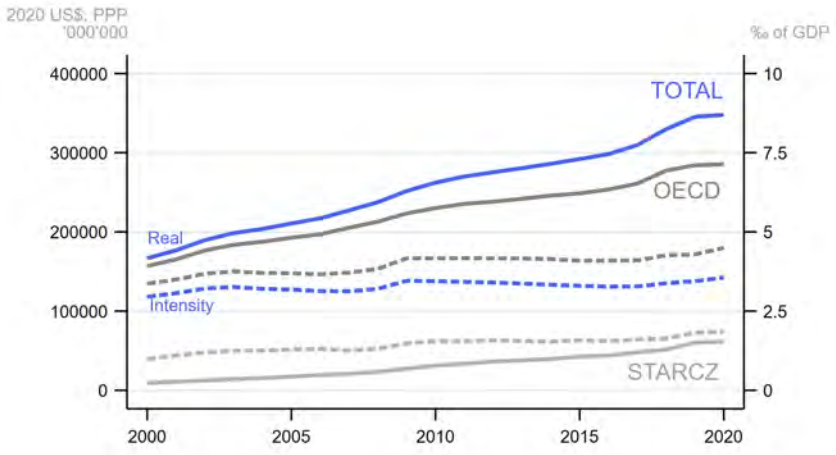
In the first two decades of this century, higher education institutions around the world received ever more funds and personnel for research and development. As reported in figure 1-1, the overall real funds across the Organisation for Economic Co-operation and Development (OECD) increased from 160bn US$ in 2000 to 290bn US$ in 2020 while those of non-OECD countries Singapore, Taiwan, Argentina, Russia, China, and South Africa (STARCZ) rose from 9bn US$ to 61bn US$. Similarly, the OECD's R&D personnel rose from 1.2 million full-time equivalents (FTE) in 2000 to 2.2 million in 2020 while that of the STARCZ rose from 300 to 800 thousand FTE. This rise was not only apparent in absolute but also in relative terms. Across all those countries, an ever larger share of GDP was allocated to higher education research that in turn employed an ever higher fraction of total employment. Crucially, 2 out of every 3 dollars were financed by the government as reported in figure A.I and that share remained stable over the two decades. At the same time, evidence from Arora et al. (2018) and Fleming et al. (2019) suggests that firms increasingly rely on government-funded research for their innovations at the expense of internal efforts, likely driven an increasing relevance of the social returns to research captured by competitors via knowledge spillovers Arora et al. (2021). This growing influence of academic research as well as its primarily public funding make a meaningful quantification of the social returns to academic research, be it via spillovers or transfers, increasingly valuable.

Due to its central role in this paper, it is paramount to establish a common understanding of academic knowledge transfers. First, both transfers and spillovers are knowledge flows from a sender, the university[1], to a receiver, the firm, but they differ in the intent of the sender. While transfers are intended, spillovers are not. This does not imply that transfers must target a specific receiver although they often do. For example, both lectures and papers intentionally disclose knowledge but the former has a clear target, the student, while the later does not. Spillovers, on the other hand, are unintended and hence always untargeted. Second, I measure transfers on a broad notion of academic activities that share the intentional flow of knowledge as their common denominator. This includes the disclosure of research results in *presentations, publications*, and *intellectual property rights*, transferring or *licensing* those rights to existing firms as part of traditional technology transfer or to newly established academic spin-offs, *consulting* those firms, conducting

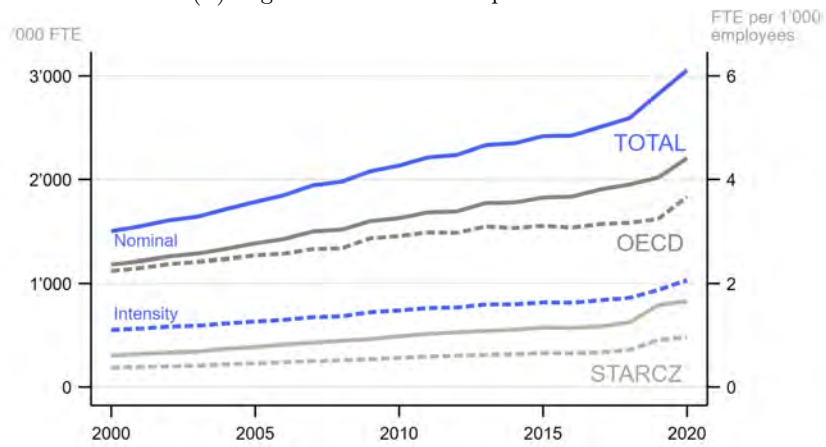
[1]For brevity, I use the notion of universities as a representative placeholder of the more general higher education institute. See table A.I for a list of all universities featured in this paper.

Figure 1-1: Higher education R&D funds and personnel

(a) Higher education expenditure on R&D (HERD)



(b) Higher education R&D personnel



Source: OECD (2024a, 2024b, 2024c), ILO (2024), author's own calculations
Note: This figure shows the higher education R&D funds and personnel in the Organisation for Economic Co-operation and Development (OECD), Singapore, Taiwan, Argentina, Russia, China, and South Africa (STARCZ), and both jointly (TOTAL). The core data stems from the OECD's data on Gross domestic expenditure on R&D (GERD) by sector of performance and source of funds for figure a, their data on R&D personnel by sector of performance and function for figure b, and their Main Science and Technology Indicators (MSTI database) for population, employment, GDP, PPP, price indices. This is augmented with employment data from the Labour Force Statistics (LFS) of the International Labour Organization (ILO) to fill data gaps. All reported values are estimates due to the unbalanced panel structure resulting from countries that report data on a non-annual basis and hence deviate slightly from the official OECD numbers. The solid lines report the absolute values measured on the left axis. The dotted lines report the relative values measured on the right axis.

contract research on behalf of them, or *collaborative research* with them, *personnel exchanges* that foster firms' research or university education, and finally, embodied transfers via *education* of students and further education of employees.[2] While most of these knowledge flows pertain to universities' modern role, their third mission of an active contribution to society, some also pertain to their traditional roles of education and research. Third, knowledge flows in all those interactions are neither exclusively transfers nor unilateral. Spillovers often accompany transfers directly or occur as second order effects if the knowledge is not kept within the recipient firm. Similarly, knowledge flows are often bilateral between universities and firms. However, the aim of these interactions is the intended flow of knowledge from universities to firms and for the sake of clarity I will refer to them as transfers. Finally, although some transfers feature the joint creation of knowledge, I base my arguments on the following stylized view. An abstract piece of knowledge is created at a university and is transferred to a firm in order to spur its research, development, and innovation. This is the core idea behind all those transfers describe above and allows for a streamlined argumentation of the causal model described below.

This paper uncovers the short-term effect of academic knowledge transfers on firm innovation. Specifically, I look at innovation inputs, measured by the extensive and intensive margin of R&D expenditures, and innovation outputs, measured by the extensive and intensive margin of sales from product innovations. As robustness checks, I use the number of employees with a tertiary education and those employed in R&D for inputs and patents and process innovations for outputs.

In an idealized research setting, universities would randomly target firms and transfer knowledge to them allowing me to identify an average treatment effect in the entire population if every firms accepted the knowledge. This intervention is infeasible as many firms would not comply. A feasible approach would randomly allocate vouchers to firms that make them eligible to receive knowledge. If universities had a perfect control over how their knowledge flows and would only hand it to eligible firms, I could identify a treatment effect on the treated, as first noted in Bloom (1984).

I do not have interventional data and rely on observational data. This makes identification trickier due to potential endogeneity issues arising from unobserved confounders. Not only do academic knowledge transfers require the intent of the university, they also feature the intent of the firm to seek that knowledge in the first place. This makes transfers highly

[2]Table A.IV contains a detailed list of everything I consider as knowledge transfers.

endogenous variables shaped by firm's strategic choices. This selection into treatment is governed by a the current economic conditions, the legal framework within which firms operate including the rules on intellectual property rights, the firm's personal and institutional network that shapes knowledge flows and especially a firm's recent research and development activities as well as their latent innovation ability. These factors likely affect a firm's current innovation inputs and outputs biasing my regression estimates if I fail to fully control for those confounders.

I use two ways to combat this confounding. First, I use panel data with two-way fixed effects for time and firm and control for a comprehensive set of start-of-period firm-level variables. Time fixed effects capture common trends that account for changed economic or legal conditions that affect all firms equally. The firm fixed effects capture idiosyncratic differences across firms that remain constant over time eliminating any bias that arises due to persistent network connections and crucially the time-invariant part in latent innovation abilities. The start-of-period variables include a firm's size, human capital, and proxy their research and innovation activities thereby partially eliminating confounding due to idiosyncratic temporal changes in latent innovation abilities.

Second, I use a shift-share instrument that exploits quasi-random variation from changes to universities' laws and regulations of intellectual property rights. These changes occurred at different times for different universities and map to firms via their spatial and technological exposure to those universities. The aim of these regulations was to foster knowledge transfer by increasing the incentives of academics to commercialize their inventions making them highly valid for my research design. This university-pushed supply shock of academic knowledge is beyond the control of firms and hence acts as an exogenous shock to them via their idiosyncratic exposures that remain almost entirely unchanged over time. Coupled with time fixed effects and the same start-of-period control vector, this instrumental variable approach eliminates biases arising due to the unobserved latent innovation ability, be it static or dynamic. This comes at the potential cost of bias due to confounding of other idiosyncratic static factors since I must loose firm fixed effects that purge the exogenous variation across firms which makes up most of the variation in the instrument.

I use Swiss observational data that spans from 1999 to 2018. My core data comes from multiple waves of firm-level surveys conducted by the KOF Swiss Economic Institute at the Eidgenössische Technische Hochschule Zürich (ETHZ) as mandated by the State Secretariat for Economic Affairs (SECO), the State Secretariat for Education, Research and Innovation (SERI), and the ETH Board. The KOF Enterprise Panel (KEP), a

stratified random sample drawn from the official Business and Enterprise Register (BER) of the Federal Statistical Office (FSO), builds the basis of those surveys. The Swiss Knowledge Transfer Survey (SKTS) measures the firm view of knowledge transfers between academia and the private sector while the Swiss Innovation and Digitalisation Survey (SIDS), the official Swiss implementation of the European Community Innovation Survey (CIS), provides start-of-period measures due to its higher periodicity. In line with the CIS and its U.S. siblings, the Annual Business Survey (ABS) and Business Enterprise Research and Development (BERD) Survey, the SKTS contains a section on general firm information including its foundation, ownership, employment, revenues, expenses, competition and the core research and development as well as innovation measures. In addition, it contains an extensive section on external knowledge sources and most centrally on academic knowledge transfer forms, partners, motives, obstacles and outcomes. These surveys yield an unbalanced panel of 6020 observations from 4293 firms.

For my shift-share approach, I augment this data with university-level administrative data. I use their corpus juris to construct the regulation shock, their building register to construct spatial exposure between firms and universities, and the FSO's censuses SHIS-PERS and SHIS-FIN to construct technological exposures and to conduct falsification test of random shock assignments.

The two-way fixed effects estimates show that academic knowledge transfers raise a firm's innovation input and output within the next 3 years where the effect on the former is larger. On the input side, transfers raise the propensity to spend on internal R&D by 14 percentage points (pp) and the internal R&D expenses by 16%. On the output side, they raise the propensity to develop a novel or improved product by 8 pp and the sales from novel or improved products by 7%. However, while the extensive margin effects are statistically significant at a 5‰ level, I fail to reject the absence of an effect for the intensive margin even at a 19% level. All in all, these first results suggest that if a firm receives academic knowledge, its innovation will benefit from it within the next 3 years. Unsurprisingly, the effect is stronger on innovation inputs than outputs since they take longer to materialize. However, it is evident that even within a respectively short time horizon innovations emerge from those transfers and to a weaker extent already generate commercial returns.

The shift-share approach first proofs that the regulations had a substantial effect on transfers and that those effects depend on time and space. The effects materialize earlier and are stronger for firms closer to the university. Within the next 4 years, regulations

only affect firms within 15km. Within 10 years, they also affect firms 15 to 100 km away. Beyond 100km, they do not seem to affect firms at all. On average, the regulations change the propensity of firms to use knowledge transfers by 65 basis points but the effects span between 0 and 4 percentage points which is substantial given the average propensity of 10% prior to the regulations. Using the shift-share instrument, the standardized point estimates inflate compared to the two-way fixed effect regressions by a factor of 4.5 to 13.1. For the intensive margin, that is due to a weak first stage and hence I cannot provide further evidence of the claims made above. For the extensive margin, the inflation is less severe and likely comes down to an insufficient excludability driven by a direct influence of the instrument on the innovation outcomes via knowledge spillovers. That is supported by regressions that better proxy for the true knowledge networks. The shift-share results clearly reject that knowledge transfers have no or negative effects on the propensity to spend on internal R&D and the likelihood to develop novel or improved products within the next 3 years and thus support the findings of the two-way fixed effects regressions.

This study contributes to three strands of literature. First, it adds to the studies on the legal framework surrounding knowledge transfers. Most notable among the is the reallocation of intellectual property rights (IPR) like in the 1980 U.S. Patent and Trademark Law Amendments Act (Bayh-Dole Act) studied in Henderson et al. (1998), Mowery et al. (2001), and Popp Berman (2008) and similar schemes in Europe as studied in Lissoni et al. (2009), Geuna and Rossi (2011), Von Proff et al. (2012), Lissoni et al. (2013), Ejermo and Toivanen (2018), and Hvide and Jones (2018). While this paper does not use the reallocation of IPR on a national level, it uses university-specific rules on the distribution of revenues from the commercialization of research. Second, it adds to the growing number of studies that apply non-random exposure to exogenous shocks (Borusyak & Hull, 2023) and especially those that apply shift-share instruments that rely on exogeneity of shocks (Borusyak, Hull, & Jaravel, 2022) or of exposures Goldsmith-Pinkham et al. (2020). Notable mentions include Bartik (1991), Blanchard and Katz (1992), Card (2001), Acemoglu and Linn (2004), Stuen et al. (2012), Autor et al. (2013), Hummels et al. (2014), Berman et al. (2017), Adão et al. (2022), Imbert et al. (2022), Xu (2022), and Mohnen (2024). Third, it adds to the literature that studies the social returns to academic knowledge via untargeted spillovers Jaffe (1989) and Mansfield (1991) and targeted transfers Beise and Stahl (1999), Stiglitz and Wallsten (1999), Jensen and Thursby (2001), Agrawal and Henderson (2002), and Cohen et al. (2002).

2 Empirical Strategy

2.1 Model

To study the short-term effect of academic knowledge transfers on firm innovation, I assume the following linear causal model[3]

$$y_{it} = \beta_0 + \beta_1 x_{it} + u_{it} \tag{1}$$

where y_{it} is firm i's end-of-period innovation input or output, $x_{it} = \mathbb{1}\{i \overset{t}{\leftarrow} \mathcal{N}\}$ is an indicator whether firm i received knowledge from any university $n \in \mathcal{N}$ during period t and u_{it} is an error term.[4] I am interested to recover the parameter β_1 but since I have no interventional data, the parameter remains unidentified as knowledge transfers x_{it} are endogenous, i.e. related to the error term u_{it}.

To best understand the problem at hand, I start from an idealized experiment. If universities would randomly target firms and transfer their knowledge to them, I could identify β_1 as the average treatment effect simply by comparing the average innovation input or output y_{it} of firms that receive academic knowledge, where $x_{it} = 1$, against those that don't, where $x_{it} = 0$.[5]

Such an intervention is infeasible since firms can refuse to comply by rejecting the knowledge. A feasible intervention would randomly allocate eligibility vouchers to firms that entitle them to receive academic knowledge. If a university had complete control

[3] Since notation is paramount for understanding, here's my convention. I denote random variables with small Latin letters that always carry subscripts denoting the dimensions over which they vary, e.g. x_{it}. I denote vectors of random variables in small boldface which are column vectors by default, e.g. $\mathbf{w}_{it} = (w_{it1} \cdots w_{itW})'$, while matrices of random variables are capital boldface, e.g. $\mathbf{W}_i = (\mathbf{w}_{i1} \cdots \mathbf{w}_{iT})$. I denote parameters with small Greek letters, e.g. β and sets in capital calligraphic Latin letters, e.g. $\mathcal{N} = \{1, \ldots, N\}$, where its size carries the same Latin letter in capitals, here N. $\mathbb{1}\{a\}$ denotes the indicator function that takes on the value of 1 if the argument a is true and 0 otherwise. Finally, I denote sums shorthand as $\sum_{a,b}$ implicitly summing over the entire set $\mathcal{A}$ and $\mathcal{B}_a$ like $\sum_{a \in \mathcal{A}} \sum_{b \in \mathcal{B}_a}$.

[4] The notation borrows from the one used in Borusyak et al. (2022) and Borusyak and Hull (2023) where i (instead of l) is the observational unit, n is the shock unit, and t measures time.

[5] Remember that I use a stylized view on transfers that builds entirely on the notion that knowledge is created at the university in isolation and transferred to firms afterwards to be developed into innovations. Some forms that I count as transfers differ from that notion in that the knowledge is co-created with firms. It is straightforward to extend the argumentation to that scenario; simply switch "transfers to firms" with "collaboration with firms". Without loss of generality, I refrain from that.

over where their knowledge flows, they could guarantee that only eligible firms receive it. As first noted by Bloom (1984), a simple comparison of average outcomes between firms with and without vouchers scaled by the likelihood that eligible firms comply identifies the average treatment effect on the treated. Since it is a university's core mission to disclose knowledge in papers and educate students, this restriction of knowledge flows is not feasible and always-takers, firms that receive academic knowledge irrespective of eligibility, are certainly present among firms without vouchers. As long as the ominous defiers, firms that receive knowledge if they don't have a voucher and vice versa, are absent, this intervention identifies at least the local average treatment effect; the effect knowledge transfers have on the innovation of complying firms.

I lack power to either intervention and rely on observational data. Identification with observational data is trickier, but in the upcoming paragraphs, I outline my approach to it that tries to mimic these interventions as best as possible.

2.2 Identification

The core issue behind identification stems from firm's strategic choice to seek academic knowledge. Transfers are thus knowledge flows of joint intent from universities and firms. This selection into treatment[6] by firms is shaped by a multitude of factors including the current economic conditions, the legal framework surrounding the firm, their personal and institutional network, and the most pivotal thing: innovation ability. With innovation ability, I imply the latent potential of a firm to innovate that is hard to measure. On the one hand, this includes institutional factors like their own expenses and stock of research and development, their network to external knowledge sources, or their pool of intellectual property rights. On the other hand, it includes factors related to their workforce like their human capital, their ingenuity including their ability to take advantage of serendipity, their personal networks, and more broadly, any skills that shape discoveries and their development into commercial returns. Whenever one of these factors causes firm's innovations y_{it} as well as their reception of academic knowledge x_{it}, they confound the relation between those variables and bias estimates of β_1 if I fail to account for the

[6]Selection into treatment is the only source of endogeneity in this study. Simultaneous causality cannot occur due to temporal restrictions. While the treatment occurs during the given period t, the outcome is measured at the end of this period. Measurement error may be a minor issue in the treatment variable due to misreporting but is likely of no concern, i.e. as long as the reader agrees on the definition of knowledge transfers. It is potentially a graver issue on the intensive margin of the outcome, as these are measured on a continuous scale, while nonexistent on the extensive margin, as those are measured on a discrete scale of 0 and 1.

endogeneity of knowledge transfers. This is especially worrisome if innovation ability raises a firm's propensity to seek academic knowledge such that in the most severe case they would come up with the same innovations even if they never received the academic knowledge.

2.2.1 Two-way fixed effects

To alleviate this bias, I use two-way fixed effects for firm and time and include a comprehensive start-of-period vector of firm-level controls that capture their size, human capital, and research and development activities. The adjusted model then reads as

$$y_{it} = \mu_i + \mu_t + \beta_1 x_{it} + \boldsymbol{\beta}_2' \mathbf{w}_{it-1} + \tilde{u}_{it} \tag{2}$$

Time fixed effects μ_t account for common trends like changes in the global or national economic and legal conditions. This includes the current business cycle, inflationary pressure and corresponding base rate changes, or changes to the value of the local currency, as well as novel taxation schemes, trade tariffs, and intellectual property protection. Firm fixed effects μ_i account for idiosyncratic differences between firms that remain constant over time. That eliminates any bias arising due to persistent differences in firm networks, e.g. from idiosyncratic differences between universities to commercialize their discoveries (Lerner, Manley, Stein, & Williams, 2024) and their spillover to firms most exposed to those universities via localization (Jaffe, Trajtenberg, & Henderson, 1993), and particularly the time-invariant part of the firm's latent innovation ability. Crucially, the innovation ability, unlike an individuals ability that confounds estimates of returns to education (Griliches, 1977), may vary over time due to changes in the workforce's composition. Hence, not all confounding from innovation abilities is annihilated with firm fixed effects. Therefore, I also use the start-of-period firm-level controls $\mathbf{w}_{it-1}$ to account for any residual time-varying confounding. This vector includes the firm's size, its human capital, its external knowledge sources, its operating margin as well as their research and development activities. This accounts for most of the time-varying confounding from the institutional part of the innovation ability like a firm's own research and development expenses and employment or their access to up- and downstream knowledge sources but fails to account for the time-varying confounding from the workforce-related innovation ability. In other words, whenever talented workers enter a company and this coincides with the firm's reception of academic knowledge, rather their skills and ingenuity are responsible for

the created innovations than the transfer. If this is a minor issue, then the recovered estimate from a regression of equation 2 is close to the true average treatment effect from knowledge transfers on firm innovation. If its a major issue, I must use an alternative identification strategy that addresses this unobserved time-varying confounding.

2.2.2 Shift-share instrument

The alternative approach closely mimics the feasible experiment described above. Instead of simple vouchers, imagine vouchers in different denominations, say by granting access to knowledge of varying value. Furthermore, imagine that each firm could shape those denominations with the restriction that they must sum to the same amount over all universities. Once each firm made its allocation, universities randomly decide whether to introduce the vouchers or not. The vouchers received by each firm then combine an exogenous set of voucher programs launched and the endogenous denominations attached to them shaped by firms. This is exactly the shift-share identification strategy popularized by Borusyak et al. (2022) and its more general framework from Borusyak and Hull (2023) that uses a common set of exogenous shocks and maps them to observation-level instruments via idiosyncratic endogenous exposures. It is also a stylized description of the real world phenomenon that I exploit here.

Between 2000 and 2020, Swiss universities gradually introduced regulations that increased their researcher's incentives to commercialize their knowledge. Those regulations lowered the costs to commercialize and the benefits accruing to inventors from commercializing. They were outside of firm influences as evident by their content that aims almost entirely at internal processes and is backed further by bilateral talks with the heads of the technology transfer offices from the most important universities. I can credibly claim that they did ex-ante act as exogenous supply shocks of commercializable academic knowledge. Each firm was affected differently by them via their idiosyncratic exposure to the universities. Formally, this results in

$$z_{it} = \mathbf{s}_{it} \cdot \mathbf{g}_t = \sum_n s_{itn} g_{nt} \tag{3}$$

where the shift-share instrument z_{it} is the dot product of a common shock vector $\mathbf{g}_t = (g_{1t} \cdots g_{Nt})'$ and the firm's exposure vector $\mathbf{s}_{it} = (s_{it1} \cdots s_{itN})'$. Each shock g_{nt} is a function of the time t_n when university n introduced the regulation, with $t_n = \infty$ if they never introduce it, and the period t. Each exposure s_{itn} is a function of firm i's spatial

and technological proximity to university n at t, with the exposures normalized to sum to 1 over the universities as $\sum_n s_{itn} = 1 \ \forall \ i, t$.

Although I argue for unconditional exogeneity of the regulations, the shocks themselves carry a temporal trend due to the fact that regulations remain valid until they cease to be in force. The instrument thus has a mechanical positive temporal trend that confounds if there is an equivalent temporal trend in firm's innovation. I modify my identifying assumption slightly such that regulations are random draws within periods and include time fixed effects in the set of variables that shape the shock expectation, i.e. $q_{nt} = (\mathbb{1}\{t = \tau\})_{\tau \in \mathcal{T}}$.[7] I assume that all other factors that govern the introduction of the regulations are not confounders and do not shape firm innovations. In section 5.1, I run falsification tests of this assumption by checking firm-level and university-level factors that may govern the regulation introductions. I only reject the null for scale effects of the administrative body of the university and of the firms surrounding them but fail to reject the null for proxies of firms' innovation ability and most importantly industry funding of universities. This strengthens the claim of instrument exogeneity and I only account for the non-random temporal trends in the instrument via a shift-share equivalent as $\sum_n s_{itn} q_{nt}$ which amounts to time fixed effects due to the normalization of the exposure vectors.

Intuitively, the instrument only varies within periods due to firms' relative exposure and the exogenous decision of universities to introduce regulations. Although firms can shape their exposures, the normalization forces a restriction on them such that a closer relative proximity to a specific university comes at the cost of a reduced relative proximity to all other universities. Coupled with the fact that firms do not adapt their exposures in response to the regulations and thus make those decisions ex-ante, it seems reasonable to assume that they never anticipated those regulations and profited from them only by their predetermined spatial and technological position. Furthermore, universities and firms are reasonably spread across the geographic and technological space such that a firm's exposure is sufficiently concentrated while universities' average exposure is sufficiently spread between them. Together with the regulations' intent of fostering knowledge transfers this guarantees that my instrument is relevant. It also guarantees

[7] As evident from equation 4, I cannot include firm fixed effects μ_i that purge all time-invariant confounding. The instrument varies mostly between firms rather than within them and firm fixed effects would eliminate this exogenous variation that helps identify the desired treatment effect. This is due to two factors. First, the shocks rely on the same underlying random variables that are distinct across universities but time-invariant. Simultaneously, within-firm changes in exposures over time are scarce due to the temporal stability in firms' spatial and technological location.

that my instrument carries enough variation for a sufficiently precise estimation and meaningful inference. I estimate the following model

$$y_{it} = \mu_t + \beta_1 x_{it} + \boldsymbol{\beta}_2' \mathbf{w}_{it-1} + \tilde{u}_{1it} \tag{4a}$$

$$x_{it} = \lambda_t + \alpha_1 z_{it} + \boldsymbol{\alpha}_2' \mathbf{w}_{it-1} + \tilde{u}_{2it} \tag{4b}$$

by two-stage least squares, where equation 4a is the structural equation and equation 4b is the first stage reduced form.

As noted in Adão et al. (2019), shift-share regressions often suffer from invalid inference caused by neglect of dependencies in the error terms between firms with similar exposure vectors. To combat this over-rejection of the null hypothesis, I follow the proposal of Borusyak et al. (2022) and run my regressions at the shock-level. This leads to the following set of equations

$$\bar{y}_{nt}^{\perp} = \mu_t + \beta_1 \bar{x}_{nt}^{\perp} + \bar{\tilde{u}}_{1nt}^{\perp} \tag{5a}$$

$$\bar{x}_{nt}^{\perp} = \omega_t + \gamma_1 g_{nt} + \bar{\tilde{u}}_{3nt}^{\perp} \tag{5b}$$

where $\bar{v}_{nt}^{\perp} = \sum_i \frac{s_{itn}}{\sum_i s_{itn}} v_{it}^{\perp}$ is the exposure-weighted average of the residualized firm-level variable $v_{it}^{\perp}$ obtained from a regression of v_{it} on μ_t and $\mathbf{w}_{it-1}$.[8] β_1 is obtained from an $s_{nt} = \sum_i s_{itn}$ weighted regression of equation 5a where the endogenous $\bar{x}_{nt}^{\perp}$ is instrumented with the shock g_{nt} directly as in equation 5b. The resulting estimate is equivalent to the one from the corresponding observation-level IV regression in equation 4.[9]

It is hard to say what constitutes the bigger problem: the unobserved time-invariant confounding accounted for by firm fixed effects or the unobserved time-varying confounding from the workforce-related innovation ability accounted for by the shift-share instrument. Both identification strategies deal with one or the other problem strengthening the credibility of the estimates. If both approaches yield wildly different results, at least one

[8] Note that I do not use regression weights in the firm-level specification such that all observations have equal weights $e_{it} \equiv 1$.

[9] Note that γ_1 in equation 5b is not the same as the first stage parameter α_1 in equation 4b. To obtain that parameter with a shock-level regression, I would need to use an s_{nt}-weighted regression of $\bar{x}_{nt}^{\perp}$ on $\bar{z}_{nt}^{\perp}$ that is instrumented with g_{nt} and controlling for time fixed effects to get the correct standard errors.

bias must be severe. If they produce similar estimates, it is likely that neither bias alone is severe.[10]

3 Data

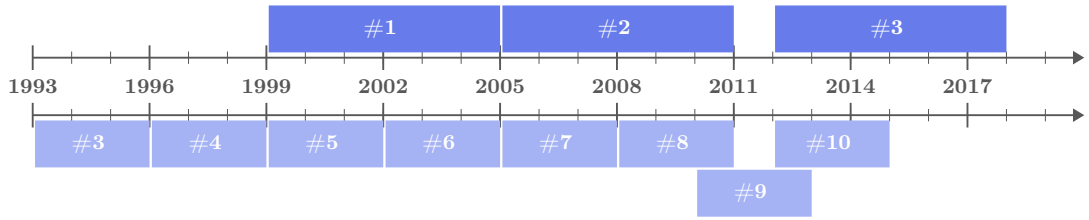
3.1 Sources

Since I do not have access to an intervention as lined out in the non-feasible and feasible experiment, I rely on observational data. The core of my data comes from firm-level surveys that I augment with university-level censuses. All data stems from Switzerland and covers the period from 1999 to 2018.

3.1.1 Firm data

My core data comes from multiple waves of firm-level surveys conducted by the KOF Swiss Economic Institute at the Eidgenössische Technische Hochschule Zürich (ETHZ) mandated by the State Secretariat for Education, Research and Innovation (SERI) and the ETH Board. The KOF Enterprise Panel (KEP), a stratified random sample representative of the Swiss economy, builds the basis of those surveys. It covers roughly 9'500 firms and is stratified on geography, industry[11], and firm size. It is drawn from the official Business and Enterprise Register (BER) of the Federal Statistical Office (FSO) and biennially updated to account for changes in the population of firms and to combat sample attrition.

Figure 3-2: Survey timeline



Note: The figure shows the waves of the SKTS and the SIDS and their coverage. The surveys were conducted within the second quarter of the year after the coverage ends, e.g. between March and June 2008 for #7. The years are labeled at their start.

[10] Another possibility is that both biases act in the same direction and are of similar size. This would yield similar point estimates that are still biased. Although it cannot be completely ruled out, it is highly unlikely.

[11] Table A.II shows the industries used and their composition of NACE sections and divisions

Swiss Knowledge Transfer Survey (SKTS) Figure 3-2 shows the 3 waves of this survey that build the basis of my dataset. They are conducted on a sexennial basis[12] and measure the firm view of knowledge transfers between academia and the private sector in Switzerland. In line with the European Community Innovation Survey (CIS) and its U.S. siblings, the Annual Business Survey (ABS) and Business Enterprise Research and Development (BERD) Survey,[13] it contains a section on general firm information including its foundation, ownership, employment, revenues, expenses, competition and the core research and development as well as innovation measures. In addition, it contains an extensive section on external knowledge sources and most centrally on academic knowledge transfer forms, partners, motives, obstacles and outcomes. Finally, it is related to the survey conducted by Bruneel et al. (2010) in the U.K.[14] but covers a broader sample representative of the entire economy. After rigorous cleaning of the data, these repeated cross-sections yield an unbalanced panel of 6020 observations from 4293 firms where 2895 are one-time participants.

Swiss Innovation and Digitalisation Survey (SIDS) Figure 3-2 shows the 9 waves of the survey I use in this study.[15] The SIDS is the official implementation of the CIS in Switzerland mandated by the SERI and conducted by the KOF. As with the SKTS, the SIDS builds upon the KEP which makes it the optimal source for additional information on research and development as well as innovation of the same firms. I use it to augment the dataset with regard to start-of-period firm-level measures.

3.1.2 University data

Table A.I shows the 23 universities that I consider in this study. They cover all higher education institutions (HEI) in Switzerland except for the universities of teacher education

[12]The funding switched between the first two and the last survey. The former were mandated and funded by the ETH Board and also covers the university view while the latter was mandated and funded by the SERI and only covers the firm view. This switch explains the one year gap between 2011 and 2012. Due to convenience, I abstract from this gap since it likely has a minor influence on my analysis.

[13]Both are conducted jointly by the U.S. Census Bureau and the National Center for Science and Engineering Statistics (NCSES) of the National Science Foundation (NSF). Their predecessors include the BRDS (2017-2018), BRDIS (2008-2017) and SIRD (1953-2007). Contrary to the CIS and the SKTS it is an annual survey instead of a biennial.

[14]In turn, the surveys of Link et al. (2007) and Bozeman and Corley (2004) in the U.S, D'Este et al. (2005) in the U.K., Landry et al. (2007) in Canada, and Landry et al. (1996) in Québec are university view equivalents where the unit of analysis are academic researchers. They are also vaguely related to the appropriation surveys from scholars of Yale (Levin, Klevorick, Nelson, Winter, Gilbert, & Griliches, 1987) and Carnegie Mellon (Cohen, Nelson, & Walsh, 2000).

[15]Currently, there exist 14 waves spanning 1990 to 2023.

(UTE). I use administrative data from the FSO's SHIS program that systematically collects information on Swiss higher education institutions and data from the universities' websites.

Corpus Juris The universities' corpus juris comprises their laws, regulations, and directives. I obtained all legal documents related to knowledge transfers through direct correspondence with the technology transfer offices, legal services, and rectorate and via their current and historic websites.[16] The direct correspondence was also invaluable to confirm the background behind the regulatory changes. Section A.II.ii provides a detailed account of the documents used and their content.

Building register I use websites of universities, departments, institutes, and chairs to build a register of facilities including their address, affiliations, and size. I use this information to create the spatial exposure of firms to each university.

University Staff (SHIS-PERS) This annual census covers university employment since 1980.[17] It features data on personnel counts, demographics, functions, and their fields of research according to the 4-digit Fields of Education and Training (ISCED-F 2013) of the United Nations Educational, Scientific and Cultural Organization (UNESCO). It is closely related to the personnel section of the Higher Education Research and Development (HERD) Survey[18] but applies to education, training, and services besides R&D. I use this data to create a firm's technological exposures to each university and to conduct falsification test of random shock assignments.

University Finances (SHIS-FIN) This annual census covers university finances since 1995.[19] It features data on revenues and expenses from the universities' income statements. It is closely related to the sources, fields, and use of funding from the Higher Education Research and Development (HERD) Survey but applies to education, training, and services besides R&D. I use this data exclusively to conduct falsification test of random shock assignments.

[16] I used the excellent Wayback Machine of the Internet Archive to access historic websites.

[17] Universities of applied sciences (UAS) were founded after 19995 and are covered since 2000.

[18] The Survey of Research and Development Expenditures at Universities and Colleges (Academic R&D Expenditures Survey) is its predecessor that ran from 1972 to 2009. As for the BERD Survey, it is conducted jointly by the U.S. Census Bureau and the NCSES

[19] Coverage of the UAS again starts from 2000.

Annual Reports (DORA) The ETH Domain's four research institutes are not part of the SHIS. I retrieve data on staff and finances from annual reports stored on their joint repository DORA.

3.2 Variables

3.2.1 Outcomes

My outcome variables y_{it} come entirely from the SKTS outlined in section 3.1.1. They are end-of-period measures of firm's innovation input $\grave{y}_{it}$ and output $\acute{y}_{it}$. I measure inputs via the R&D expenses paid for by the firm. Firms report the nominal value in CHF of their expenses at the end of the last completed fiscal year prior to the survey wave. E.g., a response of 5'000'000 in the second wave implies that the firm spent CHF 5 Million on research and development in their Swiss business units between January and December 2010. I use the natural logarithm of this nominal value as a measure of the intensive margin of innovation inputs $\grave{y}_{it}^{int}$ and a binary indicator of R&D expenses paid for by the firm in their domestic and foreign business units during the last three fiscal years for the extensive margin of innovation inputs $\grave{y}_{it}^{ext}$. For the core measure of a firm's innovation output, I use revenues from innovative products. Firms report the share of their revenues in the last complete fiscal year that comes from innovative products from the last three fiscal years. E.g., a response of 20% in the second wave implies that the firm realized 20 percent of its revenues in 2010 from goods or services that are new or improved since January 2008. The natural logarithm of the nominal value of their product innovation revenues, i.e. the share multiplied by the total revenues, serves as my measure of the intensive margin of innovation outputs $\acute{y}_{it}^{int}$ while I use a binary indicator of product innovations in the last three fiscal years for the extensive margin of innovation outputs $\acute{y}_{it}^{ext}$. Figure A.VIi to A.VIiv show the empirical densities of these variables. Section 5.2 shows how robust my results are towards alternative outcome measures.

3.2.2 Treatments

My treatment variable x_{it} also comes from the SKTS. As mentioned in section 2.1, it measures whether firm i received knowledge from any university n in Switzerland $\mathcal{N}$ outlined in table A.I during period t. As shown in figure 3-2, firms indicate if they received academic knowledge from Swiss universities via any of the forms defined in table A.IV during the prior 6 years next to information on transfer partners. I use $x_{itn} = \mathbb{1}\{i \overset{t}{\leftarrow} n\}$ to indicate if firm i received knowledge from university n during those 6 years which lets

me write the treatment variable in two ways as $x_{it} = \mathbb{1}\{\sum_{n\in\mathcal{N}} x_{itn} \geq 1\} = \mathbb{1}\{i \overset{t}{\leftarrow} \mathcal{N}\}$. E.g., $x_{i2} = 1$ means that firm i received knowledge from at least one Swiss university between January 2005 and December 2010. Figure A.VIv shows the empirical density of this variable.

3.2.3 Instrument

Equation 3 shows that the shift-share instrument is a simple dot product of a vector of shocks $\mathbf{g}_t = (g_{nt})_{n\in\mathcal{N}}$ and a vector of exposures $\mathbf{s}_{it} = (s_{itn})_{n\in\mathcal{N}}$. In other words, the idiosyncratic exposures map the common set of shocks into an observation-level metric as $z_{it} = \mathbf{s}_{it} \cdot \mathbf{g}_t = \sum_n s_{itn} g_{nt}$. As mentioned in section 2.2.2, I follow the framework of Borusyak et al. (2022) that relies on exogeneity of the shocks but allows endogeneity of the exposures.

Shocks As mentioned in section 2.2.2, I use regulatory changes at universities as shocks. For my argumentation of exogeneity it is important to understand their causes and so the historic background of efforts to promote innovations through changes in the legal framework.

In 1980, the U.S. Patent and Trademark Law Amendments Act (colloquially known as Bayh-Dole Act, henceforth BD) allowed contractors[20] to retain title over inventions resulting from government-funded research. This transferred ownership of intellectual property rights from the government to universities and federal laboratories. Although the massive increase in university patenting of the next decades was often attributed to BD, its true causes are more debatable. While BD itself and its promotion of technology transfer offices (TTO)[21] at universities are potential causes (Henderson et al., 1998), trends in industry funding (Henderson et al., 1998) or the contemporaneous gravitas of biotechnology (Mowery et al., 2001) are equally likely responsible for it. Furthermore, the Act itself is an effect of institutional changes started with the Institutional Patent Agreements (IPA) in 1968 (Popp Berman, 2008) such that the change in university patenting would likely have occurred in the absence of BD (Mowery et al., 2001). Above and beyond, there were serious doubts that the increasing in university-owned patents was driven by commercially valuable patents rather than invaluable ones (Henderson et al., 1998).

[20] That ownership was restricted to nonprofit organizations and small businesses.

[21] The Stevenson–Wydler Technology Innovation Act of 1980 was probably more influential in that promotion.

Since the start of the century, many European countries tried to emulate the apparent success of BD by adjusting their national laws regardless (Geuna & Rossi, 2011). The most dismal results came from countries that enjoyed a professor's privilege (PP) where ownership of intellectual property rights resided with its academic inventor that were now transferred to their universities. Denmark was the first country to do so in 2000 resulting in a sharp increase of patents from academic research that were mostly owned by firms, increasingly more often by universities, and less often by academics (Lissoni et al., 2009). The next countries to adopt this change were Austria and Germany in 2002. In the latter country, this had no effect on the quantity of academic patents and only resulted in a redistribution of ownership from firms and academics to universities (Von Proff et al., 2012). Norway followed suit in 2003 resulting in a substantial decline in the quantity and quality of academic patents and entrepreneurship opposed to non-university agents (Hvide & Jones, 2018) and finally Finland in 2007 with a similar drop in academic patenting (Ejermo & Toivanen, 2018). An converse route was taken in Italy where PP was introduced in 2001 and ownership went from universities to academic inventors. Sadly, this concurred with an increasing autonomy of universities including their legislation which lead to a partial rise in academic patents but mostly by a redistribution from firm ownership directly to university ownership (Lissoni et al., 2013).

The intent behind all those amendments was to spur economic growth by tapping into the unused commercial potential of scientific discoveries and turn them into innovations. The discussions surrounding that process mostly boil down to the two principal-agent problems of hidden information and hidden action and how to best address them. While a broader discussion of that follows in section 6, I outline the basics here. The principal is the society that funds the government and by extension public research. The agents are academics, universities, and the government.

With hidden information arises the problem of adverse selection. The optimal mechanism would assign ownership to the agent with the most information on the social returns of an invention. This includes information on the disclosed knowledge of the invention, the screening of the invention to decide its commercial potential, the markets for such a product, the legal process surrounding the commercialization and the social benefits accruing from the invention. Common arguments in the U.S. came from the lack of entrepreneurial culture in governments as well as its inherent inertia that guided the decision to give the ownership rights to the university. In Europe, the arguments mostly came from an ill-advised imitation of BD supported by the view that academic inventors

lacked entrepreneurial spirit or familiarity with the legal process and markets.[22] On top of that comes an administrative issue associated with the centralization of decision making. Usually, a government comprises of multiple agencies that are itself responsible for multiple universities which in turn host multiple scientists. If the government has the ownership, agencies are responsible for a bulk of decision to commercialize and hence to screen the inventions, apply for intellectual property rights, and eventually find potential firms that buy or license those rights. Universities through their TTOs would have a lower bulk of work by deciding only on the inventions made by their employees. But even under this ownership scenario, there is centralization of decision making that may end up in bottlenecks between inventors and firms that drastically slows the pace at which university-based innovations materialize (Litan, Mitchell, & Reedy, 2007; Kenney & Patton, 2009).

Another issue centers around hidden action and the associated moral hazard. Rightly noted by Jensen and Thursby (2001), most university patents are in an embryonic state and do cannot be directly turned into commercial products or processes. They require substantial follow-up investments to develop them into innovations which might lead to moral hazard. In this scenario, the firm that acquired the patent is the principal and the entity that develops it into commercial returns is the agent. With spin-offs, that issue is resolved as the principal and the agent coincide with the inventor(s). In case of technology transfer or licensing to existing firms, the problem arises once the development is not conducted by firm employees. Especially if the agent is the inventor itself, which in many circumstances is a credible assumption as they are most familiar with the inherent knowledge and so its obstacles with development, the inventor must receive royalties from the licenses or equity of the firm to be tied to the private returns from commercialization assuming the agent behaves in a purely selfish manner (Jensen & Thursby, 2001). Lach and Schankerman (2008) test that theory and show that a bigger share in royalties from licensees accruing to the inventor or the affiliated laboratory leads to greater license income. On the one hand, that is a result of strategic sorting of academics but on the other hand also the effort they put into development. It also shows that academics are motivated by pecuniary and by intrinsic motivations to commercialize their inventions.

As in the U.K., Spain, France or Greece (Geuna & Rossi, 2011), Switzerland never changed its stance on ownership. Since 1911, Art. 332 of the Code of Obligations assigns all inventions made during the course of employment to the employer without

[22] Italy was the rare decision where academics were believed to be more equipped to make those decisions (Lissoni et al., 2013).

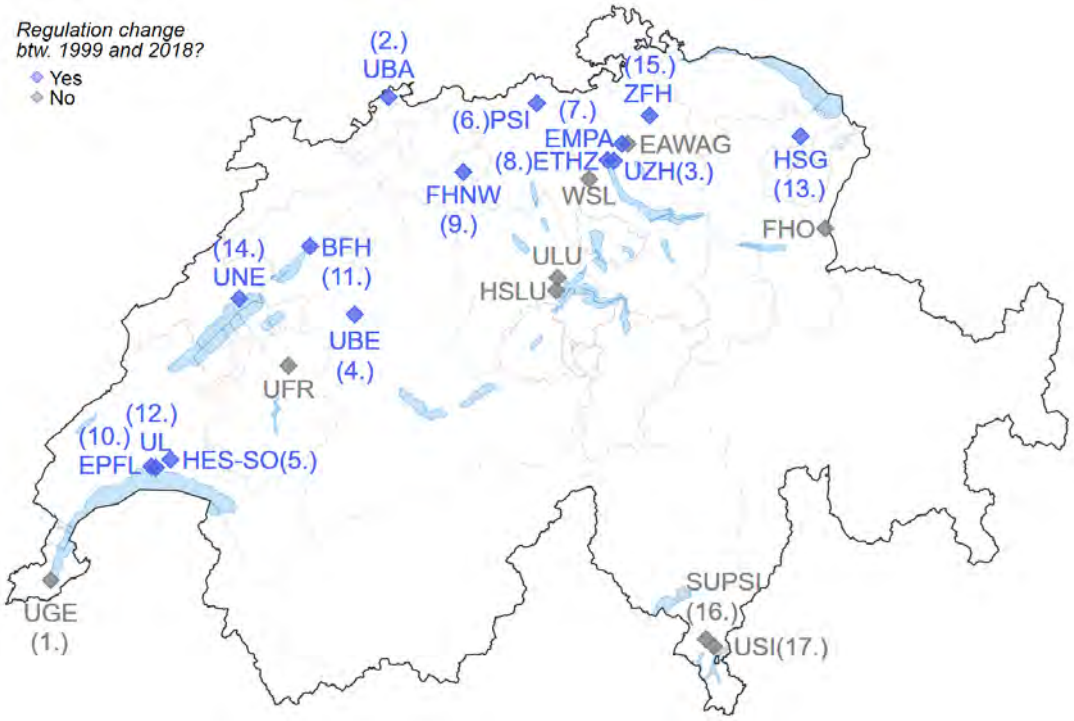
any exemptions for universities. However, concurrent with the national changes in intellectual property ownership of other European countries, Switzerland saw a gradual introduction of university bylaws and regulations that foster knowledge transfers. Those legal frameworks comprise rules on all contractual agreements that emerge with knowledge transfers. They emerged since the 1986 Federal Technology Transfer Act (FTTA) and include cooperative research agreements (CRADAs), contracts on research services like contract research or consulting, material transfer agreements (MTAs), confidentiality agreements like non-disclosure agreements (NDAs), confidential disclosure agreements (CDAs), or secrecy agreements, letter of intents (LoIs) or memorandum of understandings (MoUs), licensing or transfer of intellectual property rights (IPRs) or options on them, rules on entrepreneurship like rules on equity, preferential access to IPR or incubation, and finally rules on personnel transfers and secondary employment. Many of these contracts involve the joint creation of knowledge with a firm or commissioned by firms. They are thus of direct interest to firms and might be prone to firm interference which would make those regulations endogenous.

I focus entirely on the first explicit statement of distribution keys from returns on intellectual property rights owned by the university and hence created in isolation of firms. In line with the evidence of Jensen and Thursby (2001) and Lach and Schankerman (2008), tying inventors and their research units to the commercial returns helps overcome the moral hazard emerging from the need to further develop academic inventions. Those returns motivate inventors to help with that development and incentivizes researchers to turn their ideas into innovations. Since that distribution is a completely internal affair of universities, they are beyond firm's interests and thus likely ex-ante exogenous. Section A.II.ii contains a detailed account of these regulations including their distribution keys and the legal framework that surrounds them. Some of those regulations are part of a larger effort to stimulate knowledge transfers via the contractual agreements listed above which are of interest to firms. To alleviate doubts about firm interference in the introduction of those regulations, I conduct multiple falsification tests in section 5.1.1 that show how the timing of the regulations lacks a relation to the economic environment surrounding the respective university. Furthermore, falsification tests in section 5.1.2 alleviate second order doubts about university confounders that shape both the introduction of the regulation and firm innovation via other channels than knowledge transfers, e.g. direct or indirect knowledge spillovers.

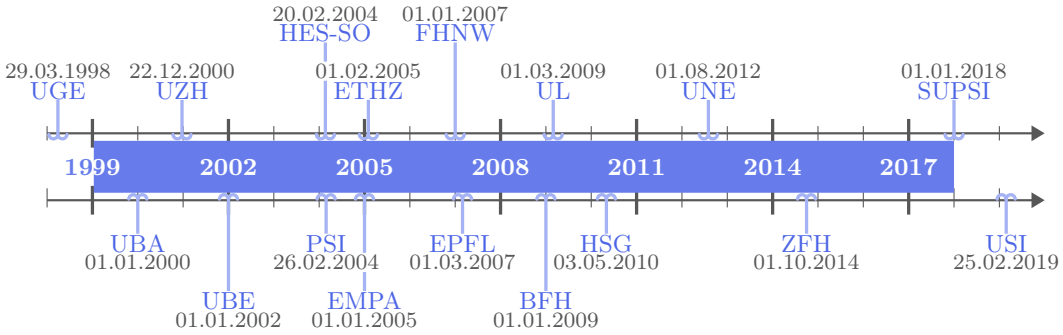
Figure 3-3 shows those regulations. Figure 3-3a depicts the spatial location of the universities in Switzerland where colored squares imply that the university introduced

Figure 3-3: Regulation enactments

(a) Map of enactments



(b) Timeline of enactments



Note: Figure 3-3a shows the spatial distribution of the shocks. The number in parentheses signals the ranking of the regulation where a lower number indicates an earlier enactment. The university in Geneva (UGE) enacted its regulation before and the two universities in Ticino (USI and SUPSI) after the observation horizon and are thus not considered in this study. Figure 3-3b shows the dates where each university's regulation came into force while the labels link to an extensive description of their incentive schemes found in section A.II.ii. The years are labeled at their start and the shaded area is the coverage of my data.

distribution keys in my observation horizon and grey squares imply the lack of that. Figure 3-3b shows the exact time when those distribution keys came into force and the numbers in brackets of figure 3-3a relate to the universities rank of introduction. Out of the 23 universities, 17 introduced keys since 1999, and 14 introduced keys in my observation horizon. While both universities in southern Switzerland introduced them after the horizon and the two universities in central Switzerland lack them to this day, all other universities show an even likelihood of such keys throughout space.[23] The timeline also shows an even distribution of those regulations over the observation horizon with somewhat of a concentration around 2005 due to the introduction of the IGBV-ETH that may had an influence on the PSI, EMPA, and ETHZ. Both figures also show the absence of a clear spatial pattern in the regulations nor one among institutes of the ETH, UNI, or UAS domain. That supports my view that those regulations are ex-ante exogenous to firms.

I denote the time where university n introduce its keys as t_n. In the main results, I assume that this timing is a random draw from a uniform distribution with support from 1998 to 2020 as $t_n \sim \mathcal{U}_{[01.01.1998,01.01.2020]}$. The shocks g_{nt} are discrete functions of those random variables. I use the two specifications

$$g_{nt} = \begin{cases} g_{nt}^{shr} & = \mathbb{1}\{t-1 \leq t_n \leq t\}\frac{t-t_n}{2190} + \mathbb{1}\{t_n \leq t-1\} \\ g_{nt}^{maj} & = \mathbb{1}\{\frac{1}{3} \leq g_{nt}^{shr}\} \end{cases} \tag{6}$$

In a slight abuse of notation, t is measured in days while in section 2 it refers to a 6 year period corresponding to a survey wave. Furthermore, I assign realizations of the random draw that fall outside of the observed interval as $t_n = \infty$ which holds similarly true for those universities that did not yet introduce a regulation but where it is assumed that they were equally likely to introduce one. g_{nt}^{shr} is simply the difference between the end of the survey wave t, e.g. the 31.12.2004 for wave 1, and the time when the keys came into force t_n expressed as a fraction of 6 years[24] and truncates that value below at 0 and above at 1. g_{nt}^{maj} is a simple metric based on the prior variable that measures if the keys were in force for at least 2 years of the period covered by the wave. The 2 year threshold comes from the insight of Aghion et al. (2024) that it takes shocks 2 to 5

[23] For those unfamiliar with the topography of Switzerland and its population distribution, I suggest the following map

[24] I take leap years into account but that would complicate the notation unnecessarily.

years to induce innovations. I use g_{nt}^{shr} to construct my instrument and g_{nt}^{maj} to assess the impact the keys had on firm's propensity to seek knowledge from that university. As the shocks g_{nt} are discrete functions of the random variable t_n and time t they feature a mechanical time trend. Once the keys are in force, they stay so. To account for that, I always use time fixed effects μ_t in my conditioning set. This then implies that shocks from the same university at different points in time are perfectly correlated conditional on t, e.g. $Cov(g_{n1}, g_{n2}|t) = 1$, since they are both discrete functions of t and the same underlying regulation that came into force at t_n. Following the notation of Borusyak et al. (2022), my core assumption is thus that the shocks are completely randomly assigned, $E(g_{nt}|q) = \mu_t$, perfectly correlated within universities, $Cov(g_{nt}, g_{n\tau}|q) = 1$, and perfectly uncorrelated between universities, $Cov(g_{nt}, g_{m\tau}|q) = 0$ if $m \neq n$, conditional on time where $q = (\mathbb{1}\{t = \tau\})_{\tau \in \mathcal{T}}$ is the conditioning set of time dummies.

This setting has multiple advantages over prior methods. In focusing on distribution keys rather than ownership rights, the legal changes should have a more clear cut effect on knowledge transfers. The gradual introduction of individual universities opposed to national laws that affect all universities at once additionally holds the advantage that I can compare outcomes of treated universities with other untreated universities. The approaches of Ejermo and Toivanen (2018) and Hvide and Jones (2018) must rely on less credible control groups that might systematically differ from universities like the government or firms. Similarly, it also allows me to compare firms that are more or less affected by those regulations depending on their exposure to universities. Recapping the stylized though experiment of section 2.2.2, firms choose the allocation of voucher denominations with a fixed total amount over universities, their exposures, and universities decide independently whether to launch that voucher series or not, the regulations.

Exposures In most shift-share applications, exposures arise naturally from the context. Designs that directly derive from shift-share analysis link national shocks to regions via their past industrial composition (Bartik, 1991; Blanchard & Katz, 1992; Autor & Duggan, 2003; Autor et al., 2013; Diamond, 2016; Mann & Püttmann, 2023; Hornbeck & Moretti, 2024), those that focus on the effects of contemporaneous migration use historic settlement patterns from external (Card, 2001, 2009; Peri, Shih, & Sparber, 2015) or internal migration (Imbert et al., 2022; Calderon, Fouka, & Tabellini, 2023), those that link consumers to products rely on the historic composition of consumption baskets by sociodemographic groups (Acemoglu & Linn, 2004; DellaVigna & Pollet, 2007; Jaravel, 2019), those that link foreign shocks to domestic firms rely on the historic composition of

imports and exports over goods-by-country pairs (Hummels et al., 2014; Dhyne, Kikkawa, Komatsu, Mogstad, & Tintelnot, 2022; Aghion et al., 2024; Garin & Silvério, 2024) and further down to productive factors via firm composition in aggregate factor payments and individuals via their factor composition in incomes Adão et al. (2022), and even studies with less conventional designs have naturally arising exposures like the composition of nationalities in scientific fields and universities used in Stuen et al. (2012), the composition of minerals in historic mines of a region used in Berman et al. (2017), the composition of banks in port financing used in Xu (2022), or the age composition of people above 45 within commuting zones used in Mohnen (2024). Linking universities to firms lacks such a natural approach since I cannot rely on historic patterns. To determine a firm's proximity to each university, I rely on their position in physical and technological space that are intuitively reasonable and frequently used in the literature. I also assume that the spatial exposure s_{itn}^{spat} and the technological exposure s_{itn}^{tech} are perfect substitutes and that the exposure is the simple weighted average

$$s_{itn} = \sigma s_{itn}^{spat} + (1 - \sigma) s_{itn}^{tech} \tag{7}$$

where I fix $\sigma \in [0, 1]$ at $3/4$ in my main specification. Section 5.2 shows how sensitive the results are to that parameter.

Spatial Spatial exposure is the result of where the firm and the university locate. Since Swiss universities look back on a long history, e.g. the UBA was founded in 1460, most firms were established long after the universities made their location choice. As such, the spatial proximity comes down to a firm's choice where to settle. While travel time would be a more accurate measure do the Swiss topography, I use the geodesic. To construct that, I geocoded the universities' and firms' addresses using Google Maps API. University addresses stem from their main buildings and hence their main campus. UAS evolved from multiple smaller institutions and roughly cover regions (NUTS-II). This leads to multi-city campuses dispersed across large areas.[25] I use the location with the biggest transfer gravitas based on prevalence of technical disciplines and geographic centrality.

[25] Multi-city campuses exist mostly for universities of applied sciences and are most sever in the case of the HES-SO, FHO, and FHNW. The first is distributed among 7 cantons and has 7 campuses in Genève, Lausanne, Yverdon-les-Bains, Neuchâtel, Delémont, Fribourg, and Sion. The second is distributed among St. Gallen, Rapperswil, Buchs, and Chur. The third is distributed among Brugg, Olten, Solothurn, and Basel. I assign the HES-SO to Lausanne, the FHO to Buchs, the FHNW to Olten, the BFH to Biel, the HSLU to Horw, the SUPSI to Manno and the ZFH to Winterthur.

In section 5.2 I check how robust my results are when I use different locations of UAS. Firm addresses stem from the mailing address of the KEP and correspond to the main location of the firm. Finally, I construct the geodesic p_{itn}[26] between the firm's location ℓ_{it} and each university's location ℓ_{nt}. Despite firm's agency over location choices, they show a high rigidity towards relocation. Out of the 4293 firms, 1398 participate in multiple survey waves and only 17% of them relocate. Figure A.IV shows the distribution of relocation distances for the 243 movers. Only 29% of those movers relocate farther than 5km, roughly the diameter of a Swiss city, and only 15% move farther than 10km, roughly the diameter of Swiss commuting zones. This implies that only 2.6% of firms where I can assess relocations ever move beyond their initial commuting zone. That is also beneficial for my purpose, as it strengthens the identifying assumptions. Firms do not relocate in anticipation of or as a response to those regulations which makes the exposures and the shocks independent.

Building on the literature in spatial economics (Brakman, Garretsen, & Schramm, 2004; Hanson, 2005; Zheng & Kahn, 2013; Ahlfeldt & Feddersen, 2018), I assume an exponential decline. Specifically, my raw spatial exposure takes the form

$$\check{s}_{itn}^{spat} = \iota * e^{\delta_n p_{itn}} \tag{8}$$

I estimate the common intercept ι, the spatial exposure in case of exact co-location, and the university-specific slopes $(\delta_n)_{n\in\mathcal{N}}$, the spatial decline of exposure, from my data to maximize its predictive accuracy of pre-regulation knowledge transfers over space.[27]

First, I estimate ι_n for each university by maximum-likelihood from the following generalized linear model with a logarithmic link function and an error term that follows a Bernoulli distribution

$$x_{itn} = e^{ln(\iota_n)+\delta_n p_{itn}} + \check{u}_{itn}$$

[26] p for $\pi o\acute{\upsilon}\varsigma$, the ancient Greek unit of length corresponding to one foot (roughly 1.01 feet in the imperial system and 0.3082 meters).

[27] If the university introduced the regulation for the majority of the observation horizon of the first wave, i.e. between 01.01.1999 and 31.12.2002, I solely use the first wave as no pre-regulation period is available.

where x_{itn} is the knowledge transfer dummy explained in section 3.2.2 and p_{itn} the geodesic between firm i and university n measured in kilometers and $\breve{u}_{itn} \sim Bern$. I then take the common intercept as the maximum of the university-specific intercepts $\hat{\iota} = max\ \{\hat{\iota}_n\}_n$ which yields .302 here. A firm that is exactly co-located with a university has a 30% probability of receiving knowledge from it.

Second, I estimate the spatial declines δ_n for each university by maximum-likelihood from the following generalized linear model with a identity link and an error term that follows a normal distribution

$$ln(\bar{x}_{ctn}) = ln(\hat{\iota}) + \delta_n \bar{p}_{ctn} + \breve{u}_{ctn}$$

where c is one of 25 equal sized sets[28] of firms from university-specific partitions of the full sample according to spatial proximity to that university, $\bar{v}_{ctn} = \sum_{i \in c} v_{itn} \,/\, |\, c\,|$ is the set-specific average of any variable v_{itn} where $|\, c\,|$ denotes the cardinality of the set, and $\breve{u}_{ctn} \sim \mathcal{N}$.[29] I partition to combat overfitting and achieve more stable estimates opposed to assuming an identical model as above on the unit level with a log link and Bernoulli error terms, especially for universities with few knowledge transfers or remote locations. After estimating the set $\{\hat{\delta}_n\}_n$, I predict the raw spatial exposure by plugging my estimates into 8. Table A.IX shows the university-specific estimates of the intercept and slopes. In line with the literature mentioned above, the spatial decline ranges between -31e-3 and -13e-3. Figure A.V shows the spatial exposure functions per university using $\hat{\iota}$ and $\hat{\delta}_n$.

Technological Hausman (2022) and Mann and Püttmann (2023) are undoubtedly the closest settings to mine. Hausman (2022) studies local economic growth induced by university research that fosters agglomeration of industries most aligned to the given university's scientific output. To link universities to industries, she builds on the effort of Kerr (2008) that relies on probabilistic concordances that assign each patent's technological area (IPC) a likelihood that it is used within a given industry (ISIC) where these likelihoods sum to one over SICs within each IPC. Mann and Püttmann (2023) go one

[28] Each set contains 100, 170, or 240 firms depending on the university and its regulation timing.

[29] Note that the average $\bar{x}_{ctn}$ has a multiplicative log-normal error term and is modelled as

$$\bar{x}_{ctn} = \hat{\iota} * e^{\delta_n \bar{p}_{ctn}} * e^{\breve{u}_{ctn}}$$

step further. While they do not focus specifically on universities, they study the effect of automation on local employment using a shift-share instrument. This instrument links aggregate changes in the stock of automation patents to commuting zones by linking patent classes to industries via concordances similar to Hausman (2022) and industries to commuting zones via their composition of lagged employment shares in those industries. Both approach builds upon the common concordances started with the Yale Technology Concordance (YTC) introduced by Evenson et al. (1991) that links the International Patent Classification (IPC) to the Canadian Standard Industrial Classification (CSIC) and the concurrent PATDAT concordance introduced by Silverman (1999) that links IPC to U.S. Standard Industrial Classification (USIC). Both efforts take advantage of the useful practice of the Canadian Intellectual Property Office (CIPO) between 1972 and 1995 to assign each patent to a technology class (IPC) as well as the industry of origin (IOM) and potential industries of use (SOU). The frequency with which each industry occurs for a given IPC is then transformed into probabilistic links via its relative frequency. The YTC was extended into the Wellesley Technology Concordance (WTC) by Johnson (1999) to accommodate simultaneous IOM-SOU links and into OECD Technology Concordance (OTC) by Johnson (2002) to link IPC to the International Standard Industrial Classification of All Economic Activities ISIC via USIC to ISIC concordances. While these concordances rely on subjective categorizations of experts on roughly 300'000 patents over nearly quarter of a decade, the MERIT concordance of Verspagen et al. (1994) and the DG concordance of Schmoch et al. (2003) build upon subjective assignments of granular IPCs to coarse ISICs based on matching the descriptions between both taxonomies. The most meaningful approach to concordances comes from Lybbert and Zolas (2014) and Goldschlag et al. (2016) for patents (IPC,CPC,USPC) and Zolas et al. (2017) for trademarks (Nice Classification, NCL). The use a data mining approach they call Algorithmic Links with Probabilities (ALP) that extracts keywords from the classifications' description of the industries and searches for those terms in the titles and abstracts of the patents. Since each patent is assigned a certain technology class, this yields frequencies with which those industries occur in a specific technology. The advantages of this approach are an independence of subjective evaluations, bilateral concordances between multiple taxonomies, and a dynamic adjustment over time and space with at low costs.

I also use a concordance approach to overcome the issue that different taxonomies categorize universities' and firms' technologies. Universities differ in their relative and

absolute scientific strength. To measure these strengths, I use the number of researchers[30] $r_{n\varphi}$ employed at university n in scientific field φ between 2017 and 2019 measured in full-time equivalents. This data comes form the SHIS-PERS described in section 3.1.2 where scientific fields Φ abide by the 149 Fields of Education and Training from the International Standard Classification of Education and Training (ISCED-F 2013) of the United Nations Educational, Scientific and Cultural Organization (UNESCO). Table A.III lists the 54 fields used in this study that are neither residual categories (69) nor irrelevant for knowledge transfers (26). The limited temporal range after my observation horizon might bias the true technological profile in the given survey wave but most universities have a fairly stable relative and absolute scientific strength.

To measure a firm's technologies, I rely on information from the SKTS and SIDS. Firms indicate if they developed any technologies in field χ from the 14 technologies $\mathcal{X}$ considered in the questionnaire and reported in table A.V. The indicator variable $d_{it\chi}$ takes on the value 1 if firm i developed any technologies in field χ in the 3 years prior to the survey wave t and zero otherwise. Unfortunately, the first wave of the SKTS did not contain that question and I rely on information from the SIDS or on imputations outlined in section A.II.i.

The last ingredient to match both realms is a concordance matrix. In line with the approaches of Verspagen et al. (1994) and Schmoch et al. (2003), the coarse technological taxonomy of the firms allows a one-to-one concordance between the 54 4-digit ISCED-F 2013 fields φ and the 14 technological fields χ. I built this concordance based on information on the web on what those technologies comprise. I measure as $c_{\chi\varphi} = \mathbb{1}\{\varphi \text{ is mostly used in } \chi\}$ the typical element of a sparse concordance matrix that assigns each scientific field the fewest number of technologies with major potential use. This results in 33 fields without a technology, 15 with exactly 1 technology, 2 with 2, 3 with 3, and 1 with 4 technologies. The re-scaled $\check{c}_{\chi\varphi}$ sum to 1 over technologies χ where fields with applications in multiple technologies are spread evenly. Table A.X shows the concordance matrix. I calculate the technological exposure as

$$\check{s}_{itn} = \sum_{\chi} d_{it\chi} \sum_{\varphi} \check{c}_{\chi\varphi} r_{n\varphi} \tag{9}$$

[30] Research assistants, scientific staff, lecturers, and professors.

This is exactly the approach of Hausman (2022), where $d_{it\chi}$ is substituted with an indicator whether a certain university n is in the vicinity of the studied region i, $r_{n\varphi}$ is the patent count of university n in IPC φ, and $c_{\chi\varphi}$ is the probabilistic concordance between IPC φ and SIC χ. The main difference is that I link universities to firms instead of industries and hence rely on my own concordance and a likely non-exhaustive measure of technologies. The advantage of my approach is that it links a finer observational unit to universities and does not rely on patents as the only measure of scientific output of a university which drastically undervalues non-technical disciplines and hence universities with a strong scientific orientation towards them. It is also advantageous in that it allows a firm to be develop technologies from multiple fields while concordance approaches rely on industrial affiliations that only measure the firms core business.

The final step to construct the exposures s_{itn} in equation 7 is to normalize the raw spatial $\check{s}_{itn}^{spat}$ and technological exposure $\check{s}_{itn}^{tech}$ from equation 8 and 9 such that they sum to 1[31] over universities as

$$s_{itn}^{spec} = \frac{\check{s}_{itn}^{spec}}{\sum_n \check{s}_{itn}^{spec}} \tag{10}$$

for both $spec \in \{spat, tech\}$. The only exception comes from firms without any technological contributions, i.e. $d_{it\chi} = 0 \ \forall \chi \in \mathcal{X}$. Their technological exposures are 0 for all universities, i.e. $\check{s}_{itn} = 0 \ \forall n \in \mathcal{N}$, and I leave them at those values without any standardization. By definition, the above formula is undefined for them and the only probable adjustment would be to distribute every technological exposure equally over universities. Since the final exposure requires both spatial and technological exposure, refraining from any adjustment implies that only the spatial proximity counts for the exposure of those firms which I judge a more sensible approach. While it is not necessary to normalize the exposures, it is convenient. Neglecting that normalization requires the need to control for the idiosyncratic magnitude of a firm's exposure $\sum_n \check{s}_{itn} \neq 1$, as the instrument carries both exogenous variation from the shocks but also endogenous differences from exposure magnitudes. Intuitively, the normalization guarantees that only the exposure composition matters and not is magnitude. As such, the instrument maps the common exogenous shocks to firm-specific measures solely due to their idiosyncratic relative exposures. Or to refer to my stylized though experiment, the total denomination

[31] Or more generally any constant that is common for firms.

of the vouchers allocated over universities is equal for all firms and they do so without anticipation of which voucher series will be actually launched. The actual value they receive is a product of the independent decision of universities and their normalized allocation. It is also not necessary to normalize the individual exposure dimensions but doing so guarantees that universities must be fairly close to a firm in both of them.

3.2.4 Controls

My control variables $\mathbf{w}_{it-1}$ come from the SKTS and the SIDS. To avoid bad controls, I use start-of-period measures that cannot be outcomes of the treatment variable except through anticipation effects. I ignore anticipation throughout my main results and show their robustness towards them in section 5.2. Whenever possible, I use data from the SKTS. This is logically infeasible for the first wave and hence I obtain those values from the SIDS. Its questionnaire shares the questions on the controls with the SKTS and they are built on the same sample of firms. This allows me to get the original start-of-period values from the SIDS.[32] As outlined in section 2.2.1, the controls account for time-varying confounders and especially those related to the firm's innovation ability. I use the firm's size of staff w^{size}_{it-1}, the staff with tertiary degrees w^{tert}_{it-1}, their export intensity[33] w^{exp}_{it-1}, their purchasing intensity w^{purch}_{it-1}, and their labor share w^{lab}_{it-1}.

Firms report their staff in full-time equivalents[34] at the end of the last completed fiscal year. My first control variable is its natural logarithm $w^{1}_{it-1} = ln(w^{size}_{it-1})$. It proxies for the firm's scope and partially accounts for its network and hence its access to suppliers, partners, competitors, distributors, customers, and external knowledge sources that also affects the likelihood of serendipitous discoveries. Subfigure i of figure A.VII shows its empirical density.

Firms additionally report their share of staff with a tertiary degree[35] at the end of the last fiscal year $\left(w^{tert}_{it-1}/w^{staff}_{it-1}\right)$. I construct my second control variable as $w^{2}_{it-1} = ln(w^{tert}_{it-1} + 1)$. The untransformed data is roughly log-normal and the addition of one allows me to retain firms without such staff. It proxies the firms human capital and partially accounts for the personal networks of the workforce. Subfigure ii shows its empirical density.

[32] I do not want to loose any observations due to missing values on control variables and hence impute the information that cannot be retrieved. Section A.II.i gives a detailed account of the procedure.

[33] I name any metric put in relation to sales as intensity.

[34] All staff-related variables are measured in full-time equivalents to account for part-time work.

[35] That includes diplomas from the professional education institutions (PEI)

Finally, firms report a bunch of financial information at the end of the last fiscal year including their share of sales from exports w_{it-1}^{exp}, their share in sales from intermediate purchases w_{it-1}^{purch}, and labor costs w_{it-1}^{lab}. I construct my third control variable as $w_{it-1}^{3} = logit(w_{it-1}^{exp})$, my fourth as $w_{it-1}^{4} = logit(w_{it-1}^{purch})$, and my fifth as $w_{it-1}^{5} = logit(w_{it-1}^{ros})$ where $w_{it-1}^{ros} = 1 - w_{it-1}^{purch} - w_{it-1}^{lab}$ is an approximation of the firm's operating margin.[36] I use the logit transformation to obtain an approximate normal distribution and to span a measure between 0 and 1 to the entire real line. Since values close to the boundaries result in heavy outliers, I truncate the R&D intensity at 10^{-5} and $1 - 10^{-5}$ before the transformation. I use this procedure for any logit transformation in this study. The third and fifth control, account for some part of the competitive environment of the firm, respectively the foreign competition through international exposure and the domestic competition for local markets expressed in the operating margin. The operating margin also accounts for the firm's financial slack and certainly drives the choice of how to use academic knowledge. Given that measure, the third and the fourth control account the firm's down- and upstream exposure, respectively. Given the same competitive pressure and financial slack, the purchasing intensity indicates a higher reliance on suppliers and governs the upstream network including the access to suppliers as external knowledge providers. The inverse applies to the export intensity that indicates the firm's international downstream network and part of its external knowledge sources from customers. Subfigure iii to v show their empirical densities. All in all, the vector of controls $\mathbf{w}_{it-1} = (w_{it-1}^{\omega})_{\omega=1}^{5}$ accounts for a heavy share of the time-varying institutional- and workforce-related innovation ability as desired.

4 Results

4.1 Two-way fixed effects

While the controls $\mathbf{w}_{it-1}$ outlined in section 3.2.4 account for a large fraction of the time-varying confounding and especially the institutional part of the firm's innovation ability, the firm-fixed effect accounts for every time-invariant confounding. I estimate β_{1y}

[36] The true operating margin, or return on sales, requires all costs of goods sold (COGS) and operating expenses (OPEX) including maintenance, depreciation, accounting, advertising, license, legal, insurance, office, or property expenses. I proxy COGS with expenses on intermediates and OPEX with labor costs. That is an imperfect approach but not the worst proxy in an economy with a high reliance on skills and services.

Table 4-1: The effect of university knowledge transfers on firm innovation

	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$
x_{it}	0.144	0.155	0.080	0.066
	(0.028)	(0.116)	(0.028)	(0.090)
$\mathbf{w}_{it-1}$	✓	✓	✓	✓
μ_i	✓	✓	✓	✓
μ_t	✓	✓	✓	✓
N	2548	541	2548	898
R^2_{adj}	0.564	0.836	0.491	0.781

Note: This table shows the estimates of β_{1y} from equation 2 for each innovation outcome y. They are outlined in section 3.2.1 and include the extensive margin of innovation inputs $\grave{y}_{it}^{ext}$ measured by an indicator of internal R&D expenses, the intensive margin of innovation inputs $\grave{y}_{it}^{int}$ measured by the natural logarithm of R&D expenses, the extensive margin of innovation outputs $\acute{y}_{it}^{ext}$ measured by an indicator of recent product innovations, and the intensive margin of innovation outputs $\acute{y}_{it}^{int}$ measured by the natural logarithm of sales from those product innovations. Neither the outcome nor the treatment variable are standardized. Observations are firm-year pairs and exclude those with controls and intensive margin outcomes in the top and bottom 5‰ to correct for outliers. Standard errors are reported in parentheses below the point estimates and are heteroskedasticity consistent. I construct all regression tables with the indispensable `eststo` and `estout` utility packages from Jann (2005, 2007).

from equation 2 by OLS implemented in STATA via the the excellent `reghdfe` package from Correia (2016) for every outcome y outlined in section 3.2.1.

Table 4-1 shows the estimates and their standard errors. The coefficients stem from the original variables which were not standardized prior to the regression. Since I lack information on when exactly the knowledge was transferred, I assume that it happens with an equal probability over the observation horizon. The results thus imply average effects of academic knowledge on firm innovation within the next 3 years which is sensible given the results of Aghion et al. (2024). First, academic knowledge raises a firm's propensity to spend on internal R&D by 14 percentage points (pp) within the next 3 years. This effect is statistically significant and I can reject a lack of effect with almost certainty. Second, academic knowledge raises a firm's internal R&D expenses by 16%. This effect is less precisely estimated and I can only reject the null at a 19% level. Third, academic knowledge raises a firm's propensity to develop a novel or improved product within the next 3 years by 8 pp. This effect is again more precisely estimated and I can reject the lack of an effect at a 5‰ level. Fourth, academic knowledge raises the sales from novel or

improved products by 7%. However, I cannot reject the absence of any short-term effect on sales even at a 46% level. All in all, these first results suggest that if a firm receives academic knowledge, its innovation will benefit from it within the next 3 years. These short-term effects are substantial, especially on the extensive margin. Unsurprisingly, the effect is stronger on innovation inputs than outputs since they take longer to materialize. However, it is evident that even within a respectively short time horizon innovations emerge from those transfers and to a weaker extent already generate commercial returns. That is especially uplifting when one regards the lack of significance as a result of the smaller sample size rather than the true absence of an effect. I must caution the reader at this point to refrain from a clear opinion on that matter as I cannot prove one or the other given the data. To strengthen those claims and account for time-varying confounding from workforce-related innovation ability not covered by the controls, I apply the shift-share approach outlined before.

4.2 Shift-share instrument

4.2.1 The effect of regulations on transfers

Before I apply the instrument to estimate the effect of transfers on innovation, I take a closer look at the first stage that seeks to uncover the effect of the regulations on transfers. Since $x_{itn} = \mathbb{1}\{i \overset{t}{\leftarrow} n\}$ measures if firm i received knowledge from university n at time t, I can study the effect of a specific universities regulation on transfers from that university as well as if this effect is heterogeneous with respect to spatial distance.

In a first step, I neglect spatial effect heterogeneity. Using a difference-in-differences (DiD) approach, I study the effect of a regulation g_{nt}^{maj} on the transfers from that university x_{itn} based on the two regression equations

$$x_{itn} = \lambda_n + \lambda_t + \dot{\gamma}_1 g_{nt}^{maj} + \dot{e}_{it} \tag{11}$$

$$x_{itn} = \lambda_{in} + \lambda_{it} + \ddot{\gamma}_1 g_{nt}^{maj} + \ddot{e}_{it} \tag{12}$$

Equation 11 uses a coarser set of fixed effects that cover university and time. The university fixed effects λ_n account for differences in transfers over universities that are persistent over time like the focus on technical sciences, size of the university, or the spatial location within Switzerland. Time fixed effects λ_t account for common trends in transfers for all

universities like government programs to foster academic knowledge exchange, easier access to that knowledge via digitization, or business cycle effects that affect the profitability of internal versus external research. $\dot{\gamma}_1$ identifies the additional transfer propensity of those universities that enact regulations opposed to those that did not. To interpret that as the causal effect of the transfer regulations on the enacting universities, I assume that each firms transfer propensity with those universities would evolve similarly to those that don't enact regulations had the prior not enacted them. More importantly, in case of staggered adoption and potential heterogeneity in treatment effects, standard DiD estimation falls victim to multiple biases as put forth by de Chaisemartin and D'Haultfoeuille (2020), Goodman-Bacon (2021), and Borusyak et al. (2024). I follow Callaway and Sant'Anna (2021) and estimate the treatment effects separately for each group of treated universities against never treated ones. In this setting that implies grouping universities according to the period when they enact the regulation as $g(n) = \sum_t t * \mathbb{1}\{\Delta g_{nt}^{maj} = 1\}$. Universities that introduce the regulation prior to 2003 are always treated units and unused here. Those that introduce it between 2003 and 2018 belong to the 2 and 3 group, i.e. $g \in \{2, 3\}$, and I estimate the equation above for both of them using universities that never introduce a regulation as controls, i.e. $g = \infty$.[37] Equation 12 additionally accounts for a finer set of fixed effects including firm specific trends λ_{it} and time-invariant firm specific transfer propensities per university λ_{in} that may arise from spatial or technological proximity.

Table 4-2 shows the estimates from both specifications individually comparing each treated group against the control. Comparing column 1 against 3 or 2 against 4 one notices that firm subscripts in the fixed effects have no significant influence on the parameter of interest. The only effect is an unsurprising increase in the explained variation of transfer patterns. The standard errors reported in chevrons cluster for university-time pairs. Since that is the unit of variation of the regulation and since they are most conservative, I rely on them to draw inference. The regulations raise the knowledge transfers with universities of the second group by roughly 1 pp. This effect is statistically significant and I can reject the absence of an effect with over 98% or 92% confidence, for the specification of equation 11 and 12 respectively. The effect on universities for group 3 is substantially lower, between 23 and 31 basis points (bp), and statistically insignificant. Whether it simply takes longer for the effects of the regulation to unfold[38] or whether effects are

[37] As the ULU was not part of the catalogue for the first two waves I have to neglect it in this section. This should not affect the results due to its minor focus on scientific fields with relevance for knowledge transfer.

[38] Note that I observe only one post period for the five universities of group $g = 3$. At the end of this period regulations are in force for roughly 7 years on average. Assuming an equal distribution of the

Table 4-2: The homogeneous effect of regulations on transfers

	x_{itn}			
	$g = 2$	$g = 3$	$g = 2$	$g = 3$
g_{nt}^{maj}	1.01	.311	.914	.226
	(0.403)	(0.518)	(0.317)	(0.459)
	[0.353]	[0.489]	[0.314]	[0.453]
	⟨0.417⟩	⟨0.410⟩	⟨0.518⟩	⟨0.469⟩
λ_n	✓	✓		
λ_t	✓	✓		
λ_{in}			✓	✓
λ_{it}			✓	✓
N	45210	39182	45210	39182
R^2_{adj}	0.039	0.015	0.476	0.449

Note: This table shows the estimates of $\dot{\gamma}_{1g}$ and $\ddot{\gamma}_{1g}$ from equation 11 and 12 separately comparing group $g = 2$ and $g = 3$ against the control $g = \infty$. Group $g = 2$ comprises all universities that enact a regulation between 2003 and 2008, group $g = 3$ those that enact it between 2009 and 2015, and group $g = \infty$ those that enact it after 2015 or never as shown in subfigure b. The transfer indicator x_{itn} is multiplied by 100 so that coefficients measure pp changes. Neither x_{itn} nor g_{nt}^{maj} is standardized. Observations are firm-year-university triples and I only use firms that take part in at least two waves of the SKTS to keep the sample sizes consistent between the first two models and the last two. Heteroskedasticity-robust standard errors are reported in parentheses, those clustered at firm-time pairs (it) in brackets, and those clustered at university-time pairs (nt) in chevrons.

highly heterogeneous between universities of the two groups is ex ante unclear. While I cannot make any claims on the former issue, I take a closer look at the heterogeneity of treatment effects hereafter.

I again compare the two treated groups $g = 2$ and $g = 3$ separately against the never treated universities $g = \infty$. The focal point of this heterogeneity analysis is the evolution of transfer propensities over time and space per university. For that purpose, I partition firms into bins based on concentric geodesic circles around the universities. I generate 15 bins per university to guarantee minimal sizes of 40 firms per university-time pair that allows meaningful inference of the true transfer propensity for firms within a specific radius. The resulting bins b_{nt} are distinct for each university-time pair. They vary over

knowledge transfers over the 6 year horizon, the average firm would only be exposed for 4 years to those regulations prior to the transfers.

universities due to the location of firms and universities across Switzerland. While bin sizes are stable, the radii behind them are not.[39] For example, the ETHZ is located in Zurich which has the highest firm density. Thus, the first 2 bins cover a radius of 12km which only covers the metropolitan area of Zurich. conversely, the remote location of the USI implies that the first bin already covers a radius of 100km that includes large chunks of southern Switzerland. The variation of bins over time within universities is smaller and entirely due to the imbalance of the sample. Despite the varying radii, the partitions always yield 15 bins. This allows me to calculate average transfer propensities over time and space for universities that enact regulations and those that do not.

First, I calculate the average propensity $\bar{x}_{bgp} = 1/I_{bgp} \sum_{n:g(n)=g,t:p(t)=p,i:b_n t(i)=b} x_{itn}$ per bin b with universities of a specific group g in a specific period p where I_{bgp} is the number of firms in bin-group-period triple.[40] The groups of universities are either $g \in \{2, 3, \infty\}$, the firms those from the partitions describe above, and the periods pre/post regulation indicators $p \in \{0, 1\}$. Depending on the treatment group under study $g^{treat} \in \{2, 3\}$, the period indicator is $p = \mathbb{1}\{t \geq g^{treat}\}$.

Second, I transform these averages in DiD estimates of bin-group specific treatment effects. I use the regression equation

$$\begin{aligned} x_{itn} &= \sum_b \mathbb{1}\{i \in b_{nt}\}(\lambda_{bn} + \lambda_{bt} + \gamma_b g_{nt}^{maj}) + e_{itn} \\ &= \lambda_{b_{nt}(i)n} + \lambda_{b_{nt}(i)t} + \gamma_{b_{nt}(i)} g_{nt}^{maj} + e_{itn} \end{aligned} \tag{13}$$

that yields the heterogeneous treatment effects $\boldsymbol{\gamma} = \{\gamma_b\}_b$ over spatial bins. For convenience, I refrain from marking these treatment effects as group specific but in effect I run two separate regressions for group 2 and 3 compared against the control. Equation 13 allows for bin specific fixed effects per university λ_{bn} and time λ_{bt} ranging between equation 11 and 12 with respect to flexibility but with the addition of heterogeneous treatment effects. To get more meaningful inference, I cluster the standard errors at the bin-university-time

[39] There is a tradeoff between fixing radii or bin sizes. Fixed radii allow inference on spatial transfer propensities over continuous space generalized across universities but come at the cost of imprecision due to low bin sizes. The converse holds true for fixed bin sizes. Since I am not interested in one parametric estimate that measures the heterogeneity of treatment effects across space, I opt for fixed bin sizes.

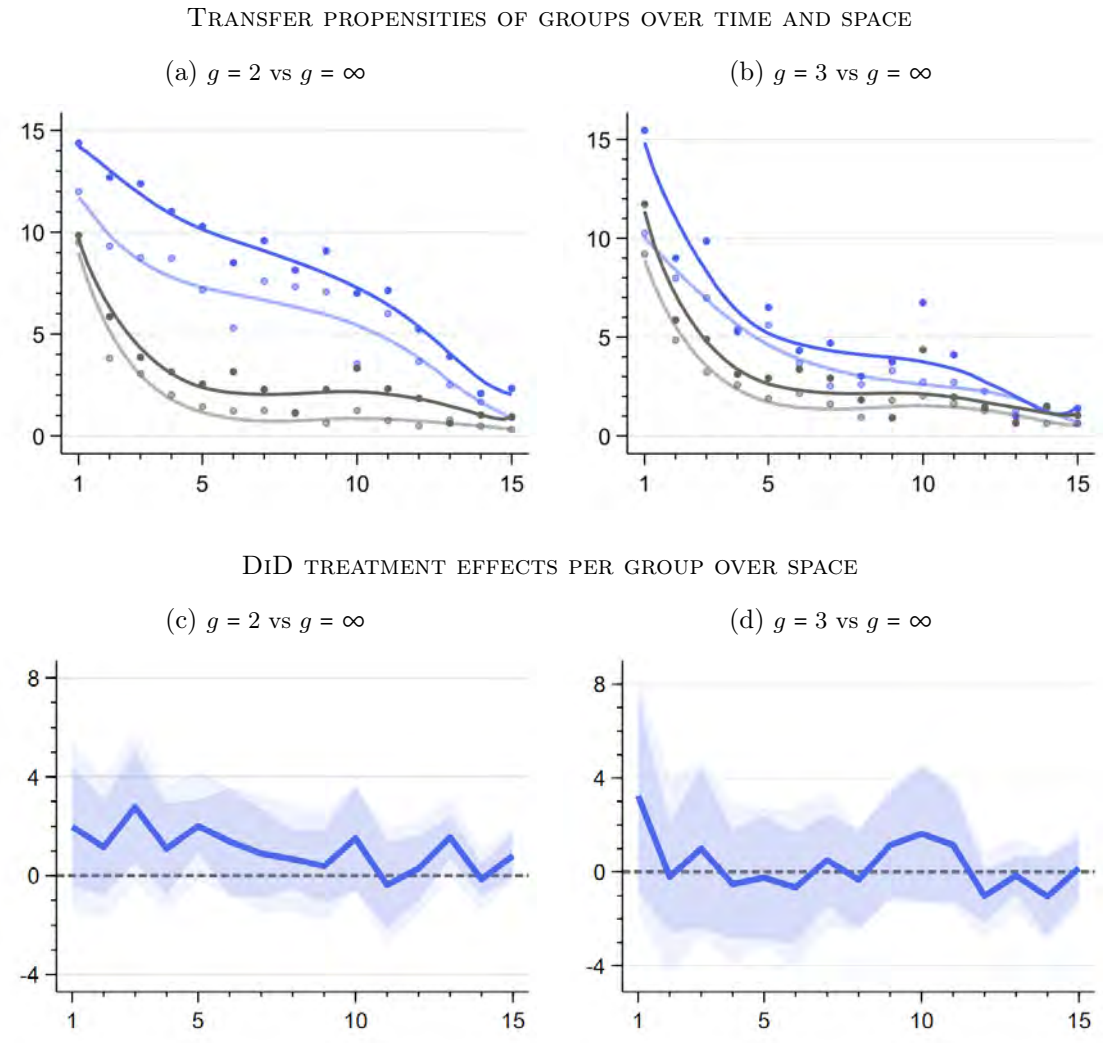
[40] Note that a firm can appear multiple times in that count but never twice from the same university-time pair. Factors within firms that jointly determine the transfers with multiple universities thus lead to dependence in the random variables x_{itn} from those averages. For that reason, I include firm clusters in the standard errors of the subsequent regressions.

level, yielding 675 cluster for $g = 2$ or 585 clusters for $g = 3$, and at the firm level, yielding 1355 clusters.

Figure 4-4 shows the heterogeneity of effects from regulations on transfer over space. The top panel includes subfigure a and b that show the bin-specific average transfer propensities $\bar{x}_{bgp}$ per group g and period p. Subfigure a compares group 2 against the never treated before and after 2005, i.e. when regulations came into force. Evident from the lines that depicted smoothed local polynomial fits, the universities that never introduce a regulation increase their propensities by roughly 1pp between those periods and this effect is approximately homogeneous over space. While my short panel structure prevents pre-trend analysis, this homogeneous temporal trend in the absence of treatment makes the estimates more credible approximations of the treatment effect. The identifying assumption of parallel trends in the absence of treatment implies that universities from group 2 would also incur a 1pp increase in transfer propensities across the bins. While this is true for bins farther away, closer bins show significantly larger increases up to 4pp. Subfigure b shows the same thing but comparing group 3 against the never treated before and after 2011, i.e. when their regulations came into force. Once again, the never treated universities show a homogeneous trend over space of about 50bp. Moreover, universities from group 3 are fairly similar to the never treated before 2011. This further strengthens the validity of the DiD approach. Ignoring the outlier in bin 10, averages evolve similar for group 3 compared to the control except for the 3 closest bins. There, the lines begin to diverge in favor of a bigger increase in transfer propensities over time.

The bottom panel includes subfigure c and d that show the estimated parameters $\boldsymbol{\gamma}_g = \{\gamma_{bg}\}_b$ from equation 13 and 90% confidence intervals from clustered standard errors at the bnt and i level. They translate the graphs from the top panel into parametric estimates by running bin-specific DiD regressions with finer fixed effects at the university n and time t level instead of group g and period p level. Although the confidence intervals suggest that the estimates are fairly imprecisely estimated, there is evidence that there is a spatial decline in treatment effects. For group 2 the regulation raises the transfer propensity in close bins by 2pp and drops to a near 0 effect for bins above 9. For group 3 the closest bin shows a treatment effect of 3pp but then quickly digresses to 0 for subsequent bins, with a one-time intermezzo for bin 10. These analysis suggest that the regulations exert heterogeneous effects on transfers which are stronger for firms closer to the university. Furthermore, there is some evidence that it takes longer for those effects to materialize for firms farther away. Within the next 4 years, regulations only affect firms within 15km while they affect firms 15 to 100 km away only within 10 years. Beyond 100km they do

Figure 4-4: The heterogeneous effect of regulations on transfers over space



Note: This figure shows the heterogeneous effect of the regulations. Subfigures a and c compare the universities that enact a regulation between 2003 and 2008 $g = 2$ against those that introduce it after 2017 or never $g = \infty$. Subfigures b and d switch the treated universities with those that enact the regulation between 2009 and 2015 $g = 3$. The top panel shows the average transfer propensity $\bar{x}_{bgp}$ of bin b with group g in period p marked as dots and corresponding lines from 3^{rd} degree smoothed local polynomial fits using Epanechnikov kernels and a bandwidth of 4. Colors label group and shading labels periods. Specifically, ● implies $g = \infty$ and $p = 0$, ● implies $g = \infty$ and $p = 1$, ● implies $g = g^{treat}$ and $p = 0$, and ● implies $g = g^{treat}$ and $p = 1$ where $p = \mathbb{1}\{t \geq g^{treat}\}$ is specific to the left and right but common within each figure. The bottom panel shows the estimated treatment effects $\boldsymbol{\gamma}_g = \{\gamma_{bg}\}_b$ from equation 13 including 90% confidence bands. Darker shaded bands ▮ stem from clustering at the bin-university-time level *bnt* while lighter shaded bands ▮ stem from clustering at the firm level i. I construct all regression figures with the indispensable `coefplot` utility package from Jann (2014).

not seem to affect firms at all. While a 2pp increase does not seem much, it must be put into relation to the average propensity between 8% and 12% in affected bins prior to the regulation. Even though my standard errors assume conservative clustering, I still caution against over-interpretation of those insights since most effects lack the necessary precision.

4.2.2 The effect of regulation-induced transfers on innovation

With the knowledge that the regulations did raise transfers, I now transform them into firm-level measures via exposures as outlined in section 3.2.3 to arrive at my shift-share instrument. I use that instrument to strengthen the claims made in 4.1 by capturing the exogenous change in knowledge transfers unrelated to the time-varying workforce-related innovation ability of firms not covered by the controls $\mathbf{w}_{it-1}$. As evident from equation 4, this comes at the cost of loosing firm fixed effects μ_i that purge all time-invariant confounding since my panel is too unbalanced for meaningful inference. Furthermore, firm fixed effects purge the biggest source of variation in the instrument which mostly varies between firms rather than within them. That is a direct effect of the way I construct my shocks outlined in equation 6 which rely on the same underlying random variable t_n within universities.[41] Another potential source of within firm variation in the instrument comes from changes in exposures over time. However, as figure A.IV and A.IIiv show, spatial and technological location of firms are fairly stable across time. Firm fixed effects would thus eliminate most variation in the instrument including exogenous variation across firms that identifies the treatment effect.

Table 4-3 summarizes the regression results from the two-way fixed effects regression as well as the shift-share instrumental variable regression. The first four columns under the heading TWFE estimate equation 2 via OLS implemented in STATA with `reghdfe` and are the standardized equivalents of table 4-1. The second four columns under the heading SSIV estimate equation 4 and 5 via 2SLS implemented in STATA with `ivreghdfe`, the `reghdfe` wrap-around of the comprehensive `ivreg2` package of Baum et al. (2002). The point estimates stem from standardized outcome and treatment variables. I report heteroskedasticity robust standard errors from observation level regressions (it) of equation 2 and 4 in brackets and heteroskedasticity robust standard errors from shock-level regressions (nt) of equation 5 in parentheses as suggested by Borusyak et al. (2022) to

[41] In many shift-share applications, the shocks are true random variables and their observations vary over time as new realizations of a random process. This generates stronger within university variation in shocks that then trickles down to firms via their exposures.

Table 4-3: The standardized effect of university knowledge transfers on firm innovation

	TWFE				SSIV			
	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$
x_{it}	0.137	0.038	0.074	0.019	0.742	0.170	0.812	-0.248
					(0.323)	(0.246)	(0.328)	(0.747)
	[0.027]	[0.029]	[0.025]	[0.026]	[0.204]	[0.316]	[0.245]	[0.493]
$\mathbf{w}_{it-1}$	✓	✓	✓	✓	✓	✓	✓	✓
μ_i	✓	✓	✓	✓				
μ_t	✓	✓	✓	✓	✓	✓	✓	✓
N	2548	541	2548	898	5044	1432	5044	2279
$N_{s_{nt}}$					52.70	49.85	52.70	50.36
N_{s_n}					18.14	16.95	18.14	17.36
F_{KP}					23.23	6.31	23.23	2.39
F_{AR}					13.91	0.29	12.30	0.30

Note: This table shows the standardized estimates of β_{1y} from 2 and 4a or 5a for the innovation outcomes y. $\grave{y}_{it}^{ext}$ is an indicator of internal R&D expenses, $\grave{y}_{it}^{int}$ is the natural logarithm of R&D expenses, $\acute{y}_{it}^{ext}$ is an indicator of recent product innovations, and $\acute{y}_{it}^{int}$ is the natural logarithm of sales from those product innovations. The first 4 columns (TWFE) are the standardized equivalents of table 4-1 and correspond to the two-way fixed effects (μ_i,μ_t) regressions with start-of-period controls $\mathbf{w}_{it-1}$ outlined in equation 2. The latter 4 columns (SSIV) correspond to the instrumental variable approach outlined in equation 4 and 5 using the shift-share instrument with shocks g_{nt}^{shr} outlined in equation 6 and σ = 3/4. Following Borusyak et al. (2022), I report robust standard errors that come from heteroskedastic shock-level regressions of equation 5 and account for error clustering for firms with similar exposures noted by Adão et al. (2019) in parentheses. The standard errors in brackets come from heteroskedasticity robust firm-level regressions. Observations N are firm-year pairs and exclude those with controls and intensive margin outcomes in the top and bottom 5‰ to correct for outliers. Following the suggestion of Borusyak et al. (2022), I report the effective sample sizes $N_{s_{nt}} = 1/\sum_{n,t} s_{nt}^2$ and $N_{s_n} = 1/\sum_n s_n^2$ corresponding to reciprocal of the exposure concentration among shocks nt or universities n, respectively. F_{KP} is the first stage F from the Kleibergen and Paap (2006) rk test and F_{AR} the reduced form F of the Anderson and Rubin (1949) test.

account for error clustering common in shift-share models due to similarities in exposures as noted in Adão et al. (2019).

The first striking observation is that the instrumentation inflates the point estimates by a factor of 5.4 for $\grave{y}_{it}^{ext}$, 4.5 for $\grave{y}_{it}^{int}$, 11.0 for $\acute{y}_{it}^{ext}$, and 13.1 for $\acute{y}_{it}^{int}$ with a sign reversal of the last estimate.[42] That is unsurprising for the intensive margins. The instrument is fairly

[42] A probable explanation behind those inflations are the low effective sample sizes. While the firm-by-time level regressions rely on 1450 to 5050 observations, the university-by-time level regressions tell a

weak for innovation inputs $\grave{y}_{it}^{int}$ and especially for innovation outputs $\acute{y}_{it}^{int}$, where $F_{KP} = 6$ and $F_{KP} = 2$ respectively. Due to this weak first stage, I sadly cannot provide further evidence for the claims made in section 4.1. If unobserved workforce-related innovation abilities are negligible confounders, I can state that knowledge transfers raise internal R&D expenses by 16% in the next three years and raise the sales from novel or improved products by 5% within the same period. If they are non-negligible, I cannot provide evidence on those effects.

That does not apply to the extensive margins. The instrument is strong for innovation inputs $\grave{y}_{it}^{ext}$ as well as for innovation outputs $\acute{y}_{it}^{ext}$ where $F_{KP} = 23$. Surprisingly, despite that strong first stage, the SSIV estimates are somewhat inflated compared to the TWFE estimates. Still, I can clearly reject that knowledge transfers have no or negative effects on the propensity to spend on internal R&D and the likelihood to develop novel or improved products within the next 3 years. The estimates for both measures are statistically significant at a 5 ‰ level using TWFE or a 3% level using SSIV.[43]

Quantifying the true effect size is harder. For the extensive margin of innovation inputs $\grave{y}_{it}^{ext}$, the TWFE estimates suggest that a one standard deviation (sd) increase in transfers raises the propensity of internal R&D expenses by .137 sd while the SSIV estimates that response at .742 sd.[44] Refraining from standardization, knowledge transfers raise a firm's propensity to spend on internal R&D within the next 3 years by 14 pp and 78 pp, with TWFE and SSIV respectively. For the extensive margin of innovation outputs $\acute{y}_{it}^{ext}$, the TWFE estimates suggest that a 1 sd increase in transfers raises the likelihood to develop novel or improved products by .074 sd while the SSIV estimates that response at .812 sd. Those estimates imply that transfers raise a firm's product innovation likelihood within the next 3 years by 8 pp or 91 pp, with TWFE and SSIV respectively. It is highly unlikely that firms can expect an effect as strong as suggested by the SSIV regression in the short

different story. $N_{s_{nt}} = 1/\sum_{n,t} s_{nt}^2$ reports the effective number of observations assuming that the shocks g_{nt}^{shr} are independent between and within universities. $s_{nt} = \sum_i s_{itn}/IT$ are the average exposures per shock in the absence of regression weights $e_{it} = 1/IT$ and IT is the number of observations in the panel. As mentioned in 3.2.3, the true random variation behind the shocks g_{nt}^{shr} does not come from shocks nt but universities n. As such, the effective sample sizes come from the concentration of average exposures to universities $s_n = \sum_{i,t} s_{itn}/IT$ among universities calculated as $N_{s_n} = 1/\sum_n s_n^2$. Evident in table 4-3, the effective sample size is 18 for the extensive margins and 17 for the intensive margins. Those numbers fall short of 20, the lower bound of shock numbers sufficient for valid inference as reported by Borusyak et al. (2022) from their MC simulations.

[43] If I use the heteroskedastic observation-level standard errors from equation 4, those estimates are significant at a 1 ‰ level. However, those errors are irrelevant due to apparent clustering from firms with similar exposures evident from heteroskedastic shock-level standard errors from equation 5.

[44] 1 sd translates to 45 pp for x_{it}, 47 pp for $\grave{y}_{it}^{ext}$, and 50 pp for $\acute{y}_{it}^{ext}$.

term (or even in long term). Due to the lagged response of innovations to shocks reported in Aghion et al. (2024), I suggest that the TWFE estimates are sensible approximations of the true short term effect, especially once put into relation to the short term effect of transfers on innovation inputs.

5 Falsification and Robustness

5.1 Falsification

The falsification tests aim to reject the randomness behind the regulation timing t_n and hence the exogeneity of the instrument z_{it}. In section 3.2.3, I argued intuitively for this exogeneity via the content of the regulations such that the shock expectation only depends on the period an nothing else, i.e. $E(g_{nt}|q) = \mu_t$ where $q = \mathbb{1}\{t = \tau\}_\tau$. While an ex-ante exogeneity is necessary, it is not sufficient. To make this claim more valid, I empirically study potential firm-level c_{it} and university-level confounders c_{nt} that jointly determine the regulation timing t_n and firm innovation y_{it}.

5.1.1 Firm-level confounders

As with any instrument, it is crucial that z_{it} is not systematically related to any unobserved confounders contained in the error term $\tilde{u}_{1it}$ of the structural equation 4a. To this end, I regress start-of-period proxies w_{it-1} of that error term and lagged dependent variables y_{it-1} on the shift-share instrument z_{it} while controlling for time-fixed effects. It is important to use start-of-period variables as every end-of-period measure is potentially caused by the regulations that are introduced during the period. As before, the correct standard errors that account for exposure clustering come from shock-level regressions.[45] This also delivers the best intuition for the present tests. $\bar{c}^{\perp}_{nt-1}$ is the time-demeaned exposure-weighted average firm-level confounder c_{it-1} where $c \in \{w, y\}$. The question thus reduces to whether there is a relation between the regulation of a given university and the average start-of-period firm environment surrounding them. For example, if c_{it-1} are the start-of-period R&D expenses of a firm $\grave{y}^{int}_{it-}$, the test hypothesizes that there is no relation between the time when a university introduces the regulation and the average R&D expenses of the firms most exposed to them.

[45] One specificity of reduced form regressions is that they translate into shock-level IV regressions of $\bar{c}^{\perp}_{nt-1}$ on $\bar{z}^{\perp}_{nt}$ instrumented with g_{nt} and controlled for μ_t while weighting by s_{nt} instead of OLS regressions of $\bar{c}^{\perp}_{nt-1}$ on g_{nt} and μ_t weighted by s_{nt}.

Table 5-4: Firm-level falsification test

	Confounders w_{it-1}					Lagged outcomes y_{it-1}			
	w^1_{it-1}	w^2_{it-1}	w^3_{it-1}	w^4_{it-1}	w^5_{it-1}	$\grave{y}^{ext}_{it-1}$	$\grave{y}^{int}_{it-1}$	$\acute{y}^{ext}_{it-1}$	$\acute{y}^{int}_{it-1}$
z_{it}	0.232	-0.020	-0.005	-0.063	0.055	0.070	-0.003	0.083	-0.005
	(0.094)	(0.045)	(0.075)	(0.067)	(0.036)	(0.059)	(0.080)	(0.091)	(0.058)
	[0.041]	[0.025]	[0.043]	[0.047]	[0.046]	[0.039]	[0.075]	[0.042]	[0.047]
w^1_{it-1}		✓	✓	✓	✓	✓	✓	✓	✓
μ_t	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	5960	5978	5889	5293	5196	6008	1960	6008	2844
R^2_{adj}	0.01	0.66	0.07	0.02	0.01	0.08	0.37	0.07	0.59

Note: This table reports the estimates from firm-level falsification tests that regress potential start-of-period (i.e. lagged by 6 years) firm confounders c_{it-1} on the instruments while controlling for time-fixed effects. The left panel uses control variables w_{it-1} from the prior regressions that are not related to firm research and development. w^1_{it-1} is the logarithm of the firm's full-time equivalents, w^2_{it-1} the logarithm of its full-time equivalents with a tertiary degree, w^5_{it-1} the logit of its export intensity, w^6_{it-1} the logit of its purchasing intensity, and w^7_{it-1} the logit of its operating margin. The right panel uses lagged outcome variables y_{it-1} from the prior regressions where $\grave{y}^{ext}_{it-1}$ is a dummy of a firm's internal R&D expenses, $\grave{y}^{int}_{it-1}$ the logarithm of those expenses, $\acute{y}^{ext}_{it-1}$ a dummy for successful product innovations, and $\acute{y}^{ext}_{it-1}$ the logarithm of sales from those innovations. The reported estimates stem from standardized regressions. The exposure clustering robust standard errors are in parentheses and those from heteroskedasticity robust firm-level regressions in brackets.

Table 5-4 shows the results of the firm-level falsification tests. In the first panel, I use the start-of-period control variables w^{ω}_{it-1} of the prior regressions that are not related to R&D, i.e. $\omega \notin \{3, 4\}$. In the second panel, I use the start-of-period outcomes y_{it-1} of the prior regressions. The regulation timing only shows a systematic relation with the firm size w^1_{it-1} surrounding a university. Once I control for that, no other variable shows statistically and economically significant relations to t_n. This is in line with the expectations from the ex-ante argumentation, the background knowledge provided in section A.II.ii, and the regulation timing reported in figure 3-3. Universities that introduce regulations earlier have similar firm environments around them than those who enact them later on. This strengthens the credibility that firms did not interfere with the introduction and that the decisions were solely driven by universities themselves.

5.1.2 University-level confounders

Specific to the shift-share design, it is also crucial that there is no unobserved confounding directly at the shock-level. Here, it implies that there are no unobserved factors within

Table 5-5: University-level falsification tests

	Staff				Funds				
	e_{nt-1}	e^{educ}_{nt-1}	e^{reas}_{nt-1}	e^{adm}_{nt-1}	f_{nt-1}	f^{base}_{nt-1}	$f^{pub:br}_{nt-1}$	$f^{pub:ar}_{nt-1}$	f^{priv}_{nt-1}
g^{shr}_{nt}	0.604	-0.049	-0.033	0.079	0.034	0.030	0.111	-0.036	0.022
	(0.125)	(0.104)	(0.053)	(0.029)	(0.021)	(0.024)	(0.096)	(0.120)	(0.075)
e_{nt-1}		✓	✓	✓	✓	✓	✓	✓	✓
μ_t	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	69	69	69	69	69	69	69	69	69
R^2_{adj}	0.24	0.62	0.90	0.96	0.98	0.98	0.66	0.24	0.73

Note: This table reports the estimates from university-level falsification tests that regress potential start-of-period (i.e. lagged by 6 years) confounders c_{nt-1} on the shocks g^{shr}_{nt} while controlling for time-fixed effects. The left panel uses the university's staff $e_{nt-1} = e^{eudc}_{nt-1} + e^{reas}_{nt-1} + e^{adm}_{nt-1}$ that comprises the teaching staff e^{educ}_{nt-1} (Cat. 51 & 52 of the SHIS staff categories), assistants and the scientific staff e^{reas}_{nt-1} (Cat. 53 & 54), and the administrative and technical staff e^{adm}_{nt-1} (Cat. 56 to 59). The right panel uses funds $f_{nt-1} = f^{base}_{nt-1} + f^{pub}_{nt-1} + f^{priv}_{nt-1}$ that comprises base funding f^{base}_{nt-1}, third-party public funds f^{pub}_{nt-1} for basic $f^{pub:br}_{nt-1}$ or applied research $f^{pub:ar}_{nt-1}$, and third-party private funds f^{priv}_{nt-1}. The reported estimates stem from standardized regressions with natural logarithms applied to all staff and funds metrics. Heteroskedasticity robust standard errors are in brackets.

universities c_{nt} that govern the regulation timing t_n as well as firm innovation y_{it} via similar exposures s_{itn} than those which matter for the instrument z_{it} as $c_{it} = \sum_n s_{itn} c_{nt}$. The last distinction is crucial. The shocks must not be completely random but only random with regards to unobserved innovation ability of the firm. To this end, I regress potential start-of-survey, i.e. 1999 values, university-level confounders directly on the shocks g^{shr}_{nt} while controlling for time-fixed effects. Once I know which factors govern the regulation enactment, I then argue for their independence of unobserved firm-level innovation ability.

Table 5-5 shows the results of the university-level falsification tests. In the first panel, I use the universities' start-of-period staff composition measured in full-time equivalents that I get from the SHIS-PERS outlined in section 3.1.2 and completed with annual reports from the online repository DORA outlined in section 3.1.2. In the second panel, I use the universities' start-of-period funds composition retained from the SHIS-FIN outlined in section 3.1.2 and completed with annual reports from the online repository DORA outlined in section 3.1.2. Similar to the firm-level falsification tests, only the size of the university is predictive of the regulation timing. While the academic staff comprising of the teaching staff e^{educ}_{nt-1} and the scientific staff e^{reas}_{nt-1} are irrelevant for the

regulation enactment, the absolute and relative size of the administrative staff e_{nt-1}^{admin} is decisive. Larger universities and especially those with a heavy administrative force enact earlier. Conversely, the funds per employee as well as their sponsor are irrelevant for the enactment. Most important, third-party private funds show effects close to zero that are statistically insignificant even at a 25% level. Thus, I can clearly reject that firms did interfere with the regulations via financial contributions. Coupled with the insights of table 5-4, it is credible that firms did not interfere at all.

Both falsification tests show that the only thing that matters for the regulation enactment is size. Larger universities enact earlier and are surrounded by larger firms. These scale effects are likely accompanied by spatial effects, such that the regulations appear earlier on in larger cities. Since larger firms have larger networks and larger cities are home to broader networks, it is likely that the main reason for the inflation behind the estimates of table 4-3 stems from a failure of the exclusion restriction. The regulations do not only affect a firm's innovations via targeted knowledge transfers but also over untargeted knowledge spillovers that depend on the firm's network. While I lack data on firm networks and especially knowledge networks, I can still provide some evidence for that hypothesis by controlling for all start-of-survey variables that proxy for the firms network, i.e. w_{it-1}^{1}, w_{it-1}^{2}, w_{it-1}^{3}, and w_{it-1}^{4} as described in section 3.2.4, as well as the end-of-period shift-share averaged university sizes $e_{it} = \sum_n s_{itn} e_{nt}$.

Table A.XI shows that the point estimates of the extensive margins deflate with the novel approximation of a firm's network although at the cost of a lower precision. The intensive margin measures remains unfit for the shift-share instrumentation. These results suggest that a better approximation of the latent untargeted knowledge flows might indeed reduce issue of partial excludability. Since the point estimates move closer to the TWFE results, the SSIV strategy seems to concur with effect sizes of the former approach and I rely on those measures to quantify the true effects.

5.2 Robustness

5.2.1 Leave-one-out

To assess the influence of each university on the results, I estimate the SSIV model from equation 4 and 5 using an instrument that drops one university at a time. Figure A.VIII reports the leave-one-out estimates including the benchmark model that uses all universities as reported in table 4-3. Overall, the results are robust to the omission of

each university. I can clearly reject that certain universities drive the results and alleviate doubts that only large universities with a strong focus on engineering like the ETHZ or the EPFL matter.

5.2.2 Alternative exposures

To assess the sensitivity of the results towards the weight σ put on the spatial exposure in creation of the instrument as reported in equation 7, I estimate the SSIV model from equation 4 and 5 using parameters that range from 0 to 1 in steps of $1/24$. Figure A.IX reports the estimates including the benchmark model that uses $\sigma = 3/4$ as reported in table 4-3. While the extensive margin of subfigure i and iii are sensitive to that weight, the intensive margin of subfigure ii and iv is not. For the extensive margin, putting full weight on the spatial exposure, i.e. $\sigma = 1$, yields point estimates close to zero that are statistically insignificant. Conversely, putting full weight on the technological exposure, $\sigma = 0$ produces very high point estimates that are highly significant. Especially in case of the innovation output $\acute{y}_{it}^{ext}$, the point estimate massively overshoots 1 which is logically impossible and is only feasible due to the identity link of the model. Between those extrema, a higher weight put on the technological exposure, i.e. a smaller σ, monotonically and convexly increases the point estimate while the confidence band is fairly stable to the parametric constellation. I trust the results from a moderate weight on technology, i.e. $1 - \sigma = 1/4$, and a heavy weight on space, i.e. $\sigma = 3/4$. Technology seems to play a role in the true exposure of a firm towards the transfer regulations of universities but heavy weights are unreliable. That is probably due to the equal distribution of technological weights to firms without technological activities and a more accurate measure of technological exposure could alleviate this bias.

5.2.3 Alternative outcomes

To provide a broader scope of the effects from academic knowledge transfers on firm innovation, I apply different innovation measures y_{it}. On one hand, it alleviates doubts that the effects shown in table 4-1 and 4-3 are specific to R&D expenses and product innovations instead of innovation inputs and outputs in general. On the other hand, it extends the treatment effects to a broader set of variables that might be more relevant in different contexts. My alternative measures for innovation inputs $\grave{y}_{it}$ include an indicator of R&D staff at the end of the last completed fiscal year, $\grave{y}_{it}^{ext}$, and the natural logarithm of the R&D staff at the end of the last completed fiscal year measured in full-time-equivalents, $\grave{y}_{it}^{int}$. The alternative measures for innovation outputs $\acute{y}_{it}$ include an indicator of successful

process innovations in the last three fiscal year, $\acute{y}_{it}^{ext}$, and the cost reductions from those innovations in the last fiscal year measured in percentage points, $\acute{y}_{it}^{int}$. Additionally, $\check{y}_{it}$ measures the innovation intermediates via the presence of any patent applications in the last three fiscal years, $\check{y}_{it}^{ext}$.

Table A.XII reports the estimates of β_{1y} using the two-way fixed effects approach lined out in equation 2. I refrain from the shift-share regressions of equation 4a and 5a here because the instrumentation only works for the extensive margin. The effect size is identical for innovation inputs $\grave{y}_{it}$ whether I employ R&D expenses or staff. Transfers raise the change to spend on and employ staff in R&D by 14.4 pp. On the intensive margin, transfers raise R&D expenses by 16% and the R&D staff by 9%. The extensive margin effects are statistically significant even at a 1‰ level. The intensive margin effects fail to be statistically significant at a 18% level. Combined, the results clearly show that knowledge transfers from a university to a firm raise their short-term innovation inputs with a strong effect on the extensive margin $\grave{y}_{it}^{ext}$ and smaller and vaguer effect on the intensive margin $\grave{y}_{it}^{int}$.

The effect sizes are somewhat different for innovation outputs $\acute{y}_{it}$ if measured by product of process innovations. This is not surprising since product and process innovations are distinct outcomes while R&D expenses and staff are closely linked inputs. Transfers raise the success of product innovations by 8 pp while they raise those of process innovations by 14.8 pp. Both extensive margin measures are statistically significant at 5‰ level. Conversely, both intensive margin measures fail to be statistically significant even at a 46% level. The point estimates suggest that transfers raise the sales from novel or improved products by 6.6% and reduce the production costs by 0.1 pp. The low economic significance supports the view that within three years from the transfers, the intensive margin of innovation outputs remains unaffected. Combined, the results clearly show that knowledge transfers from a university to a firm raise the short-term success of developing innovations but fail to deliver economic returns (yet).

Last, transfers raise the likelihood to apply for a patent by 8.8 pp within the next three years. This effect is statistically significant at a 1‰ level. As such, academic knowledge transfers exert strong short-term effects on a firm's innovation inputs, intermediates, and outputs. This applies in particular to the extensive margin of those measures. Higher expenses on internal R&D and especially commercial returns from innovations fail to materialize within the short term.

5.2.4 Sample split

As a last check, I split my sample and only rely on firms that pursued innovations in the past irrespective of the actual innovation success. The exclusion of the firms that never pursued innovations serves three goals. First, it eliminates a large chunk of firms that do not receive academic knowledge since they have no use for it. This might bias the control group in the direction of less innovation ability if it is not time-invariant or taken up by the start-of-period control vector. Second, it raises the relevance of the instrument since the firms that likely remain unaffected by the regulations are excluded. Third, it delivers a treatment effect that is more aligned with the desired policy effect. If a similar voucher scheme as described in section 2.1 were launched, the relevant effect of that policy would be its impact on firm innovation for firms that actually profit from such knowledge. It is meaningless to hand out voucher to SMEs that provide local non-durable services as they would simply discard the voucher. The desired policy effect thus aims at the effect of transferring academic knowledge to firms that have some innovation interest and ability.

Table A.XIII shows the version of table 4-3 using the restricted sample. The TWFE results are fairly stable to that restriction. Using the unrestricted sample, transfers raise the likelihood of internal R&D expenses by 14 pp, the R&D expenses by 16%, the success of product innovations by 8 pp, and the sales from novel or improved products by 7%. Using the restricted sample, those numbers change to 14 pp, 16%, 6 pp, and 9%, respectively. The significance of the results is equal across samples for the innovation inputs but less so for the outputs. This is unsurprising since the restriction excludes firms without prior innovation experience and hence affects product innovations stronger than R&D expenses. Despite that, the stability of the results towards the sample restriction gives credibility to the approach from equation 2. The bias induced by the latent innovation ability of a firm is well accounted for by the firm fixed effects that purge static differences and the start-of-period control vector that takes care of dynamic differences.

The SSIV results are also insensitive towards the sample restriction. The extensive margin measures deliver almost identical point estimates with similar precision. The intensive margin measures are somewhat distinct. The scope of the effect on R&D expenses is halved and the estimate reverses its sign from positive to negative if I use the restricted sample. Similarly, the effect on sales from innovative products reverses its sign from negative to positive and its scope falls by a magnitude such that it is almost identical with the TWFE effect if I employ the restricted sample. However, the failure to reject the absence of any effects grows tremendously such that all intensive margin effects fail to

even pass the 50% significance level. Finally, the first stage with the restricted sample is stronger for the innovation outcomes as expected indicating that the regulations exerted a stronger effect on firms that already had innovation experience.

Overall, the sample restriction confirms the prior findings. This implies that the found effects are close to the policy effects of interest and that especially that the TWFE approach delivers meaningful approximations of the true causal effect of academic knowledge transfers on firm innovation.

6 Conclusion

The contributions of this paper are twofold. First, I show that the universities' gradual introduction of transfer regulations since the turn of the century was a success. On average, the regulations raised the average likelihood of a firm to seek academic knowledge by 65 basis points. Within the 4 years after their enactment, they only affect firms within within a 15km radius and leave firms beyond 100km unaffected. The effects are also stronger the closer a firm gets to a university with a maximal 4 percentage point change in the transfer likelihood for the closest proximity. Second, I show that academic knowledge transfers, directed knowledge flows from a university to a firm, raise the innovation inputs and outputs of the recipient firm within the next 3 years. Two-way fixed effects panel regressions suggest that transfers raise the likelihood to spend on internal R&D by 14 percentage points (pp) and the internal R&D expenses by 16%. They also raise the propensity to develop a novel or improved product by 8 pp and the sales from novel or improved products by 7%. An instrumental variable regression using a shift-share instrument that maps the university regulations to firms via their technological and spatial proximity supports the extensive margin effects but fails to deliver significant results on the intensive margins.

These results contribute to the literature in two ways. The regulations and their impact on transfers are relevant to the discussion on the optimal incentive structure in public research. The main argument revolves around the public good nature of knowledge and the associated market failure due to positive externalities via spillovers that cannot be privatized by its creator. If left to profit maximizing firms, this results in an investment in knowledge below the social optimum and legitimizes public investments in research via government labs or universities. Innovation policies thus heavily focus on promotion of knowledge creation and dissemination in public institutions via incentive structures

like intellectual property rights (IPR). One prominent example is the 1980 U.S. Patent and Trademark Law Amendments Act (Bayh-Dole Act) that shifted ownership rights of inventions from government-funded research from the government to the inventing institution, mostly the universities and federal labs. Although many studies attribute large positive effects in academic patenting and entrepreneurship on the Bayh-Dole Act, there is evidence that trends in industry funding (Henderson et al., 1998) and the contemporaneous gravitas of biotechnology (Mowery et al., 2001) are equally responsible and that the Act itself is a result of institutional changes that started in 1968 (Popp Berman, 2008). Imitation efforts in Europe since the turn of the century that abolished ownership by academic inventors in favor of university ownership proofed fruitless (Von Proff et al., 2012) or even detrimental (Ejermo & Toivanen, 2018; Hvide & Jones, 2018). My results show that beyond federal laws on IPR ownership, university specific regulations on revenue distribution from commercial returns of inventions can promote knowledge transfers within a relative short-term but remain spatially concentrated. While the latter result may be due to the Swiss federalism, it seem plausible that other incentive structures beyond IPR promote academic knowledge flows that are essential for the argument of public funding. Although that result is uplifting and gives policy makers a further tool to promote regional innovation and growth, it would be interesting to see what would happen if Switzerland would adopt a professor's privilege that proofed highly valuable and effective in Germany, Norway, and Finland since it gives ownership to the person most familiar with the invention and resolves the principal-agent problem of developing the raw inventions into innovations (Jensen & Thursby, 2001; Lach & Schankerman, 2008).

The second contribution is towards a quantification of the social returns from academic research. While the social returns arguably include many more avenues than directed transfers to one firm, it is a minimal requirement of the effectiveness of said knowledge for innovation. If even targeted knowledge flows, including research and development co-operation between a university and a firm, would fail to deliver any positive effects on innovation outputs, it would be unlikely that untargeted spillovers via public dissemination of knowledge in patents or publications would achieve that feat. However, my results suggest that beyond a substantial short-term effect on innovation inputs, transfers also raise the innovation outputs as measured by product and process innovations. While I agree with Bozeman (2000) that the most important effects prevail over a longer horizon, short-term effects are a welcome sight. Similarly important, the evidence that transfers not only raise internal R%D expenses but also motivate some firms to start their internal R&D efforts is crucial for a well functioning innovation system. Without the capacity to

absorb academic knowledge (Cohen & Levinthal, 1989), firms cannot profit from it. As such, the public good becomes a club good where firms without the necessary absorptive capacity are excluded from its consumption. For the most meaningful innovation system, it is thus paramount that firms maintain that capacity by their own internal R%D efforts or by joint R&D efforts with external agents. Otherwise, public investments in knowledge creation are economically fruitless since they fail to trickle down to firms via spillovers.

While this is one effort to contribute to a quantification of the social returns to academic knowledge it is clearly not a complete and final one. In fact, I mostly estimate the private short-term returns to the firms. The social return includes the consumer and producer surplus of that innovation for the duration of its existence, any future innovation that builds on that innovation, any other transfers of that invention to other firms, any spillover to other firms, as well as any future scientific discoveries spurred by that invention. While that seems daunting to correctly quantify, it would be highly beneficial for the most accurate policy. The debate between private and social returns to research lie at the heart of the debate about public research funding. A systematic underestimation of the social return would direct insufficient means to universities and deliver a suboptimal innovation and hence growth rate. At last, it would also be paramount for one of the more interesting incentive schemes for innovation: patent buyouts as suggested by Kremer (1998)

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A Appendix

A.I Background information

Swiss Higher Education Institutions

Table A.I: Universities and their location

Federal Institutes of technology (ETH) and affiliated research institutes		
ETHZ	Eidgenössische Technische Hochschule Zürich	47°23'N 8°33'E
EPFL	École Polytechnique Fédérale de Lausanne	46°31'N 6°34'E
PSI	Paul Scherrer Institut	47°32'N 8°14'E
EAWAG	Eidg. Anstalt für Wasser., Abwasser. & Gewässerschutz	47°24'N 8°37'E
EMPA	Eidg. Materialprüfungs- & Forschungsanstalt	47°24'N 8°37'E
WSL	Eidg. Forschungsanstalt für Wald, Schnee & Landschaft	47°22'N 8°27'E
Universities (UNI)		
UBE	Universität Bern	46°57'N 7°26'E
UBA	Universität Basel	47°34'N 7°35'E
UFR	Université de Fribourg	46°48'N 7°09'E
UGE	Université de Genève	46°12'N 6°09'E
UL	Université de Lausanne	46°31'N 6°35'E
ULU	Universität Luzern	47°03'N 8°19'E
UNE	Université de Neuchâtel	47°00'N 6°56'E
HSG	Universität St. Gallen	47°26'N 9°23'E
USI	Università della Svizzera italiana	46°01'N 8°57'E
UZH	Universität Zürich	47°22'N 8°33'E
Universities of applied sciences (UAS)		
BFH	Berner Fachhochschule	47°09'N 7°15'E
FHNW	Fachhochschule Nordwestschweiz	47°21'N 7°54'E
FHO	Fachhochschule Ostschweiz	47°10'N 9°28'E
HSLU	Hochschule Luzern	47°01'N 8°18'E
HES-SO	Haute école spécialisée de Suisse occidentale	46°32'N 6°39'E
SUPSI	Scuola universitaria professionale della Svizzera italiana	46°02'N 8°55'E
ZFH	Zürcher Fachhochschule	47°30'N 8°43'E

Note: This table contains the higher education institutions (HEI) in Switzerland I consider in this paper. This explicitly excludes the universities of teacher education (UTE) as they are negligible with respect to knowledge transfers. All institutions are public and receive their core funding from the state. The ETH and its affiliated research institutes receive most funds directly from the central government, the UNI from cantonal governments (NUTS-III), and the UAS from inter-cantonal coalitions (close to NUTS-II). The coordinates are rounded to minutes and correspond to the location with the biggest knowledge transfer gravitas.

NACE

Table A.II: Industries and their NACE equivalents

Industry	NACE	Description	Sample Share
1	10, 11, 12	Food / Beverages / Tobacco	4.8
2	13, 14, 15	Textiles / Clothing	1.3
3	16, 17	Wood / Paper	2.8
4	18	Printing	2.2
5	19, 22	Coke & Refined Oil / Rubber & Plastics	2.2
6	20	Chemicals	2.7
7	21	Pharmaceuticals	1.3
8	23	Non-metallic Minerals	1.7
9	24	Basic Metals	1.4
10	25	Fabricated Metals	7.5
11	26	Electronic & Optical Products	7.4
12	27	Electrical Equipment	2.7
13	28	Machinery	8.0
14	29, 30	Vehicles	0.9
15	31, 32	Other Manufacturing	3.2
16	33, 45	Repair & Installation	1.9
17	D, E	Energy / Water & Waste	2.6
18	41, 42	Construction & Civil Engineering	4.7
19	43	Specialized Construction	5.8
20	46, 47	Wholesale & Retail	8.0
21	H	Transportation & Storage	6.2
22	58, 59, 60	Publishing & Broadcasting	2.0
23	61, 62, 63, 95	Information & Communication Technology	1.4
24	K	Financial & Insurance Services	6.2
25	L, M w/o 71 & 72	Professional Services	3.3
26	71, 72	Technical & Scientific Services	4.6
27	I, N, 96	Other Services	3.2

Note: This table shows the composition of the 27 industries that build one of the strata dimensions of the KEP. The industries group NACE sections (I-digit) and divisions (II-digit) that yield a representative picture of the Swiss economy.

ISCED-F 2013

Table A.III: Scientific fields Φ

φ	Description
0111	Education science
0113	Teacher training without subject specialisation
0114	Teacher training with subject specialisation
0211	Audio-visual techniques and media production
0212	Fashion, interior and industrial design
0213	Fine arts
0214	Handicrafts
0215	Music and performing arts
0221	Religion and theology
0222	History and archaeology
0223	Philosophy and ethics
0231	Language acquisition
0232	Literature and linguistics
0311	Economics
0312	Political sciences and civics
0313	Psychology
0314	Sociology and cultural studies
0321	Journalism and reporting
0322	Library, information and archival studies
0412	Finance, banking and insurance
0413	Management and administration
0421	Law
0511	Biology
0521	Environmental sciences
0531	Chemistry
0532	Earth sciences
0533	Physics
0541	Mathematics
0613	Software and applications development and analysis
0711	Chemical engineering and processes
0712	Environmental protection technology
0713	Electricity and energy
0714	Electronics and automation
0715	Mechanics and metal trades

Table A.III: (continued)

φ	Description
0716	Motor vehicles, ships and aircraft
0721	Food processing
0722	Materials (glass, paper, plastic and wood)
0731	Architecture and town planning
0732	Building and civil engineering

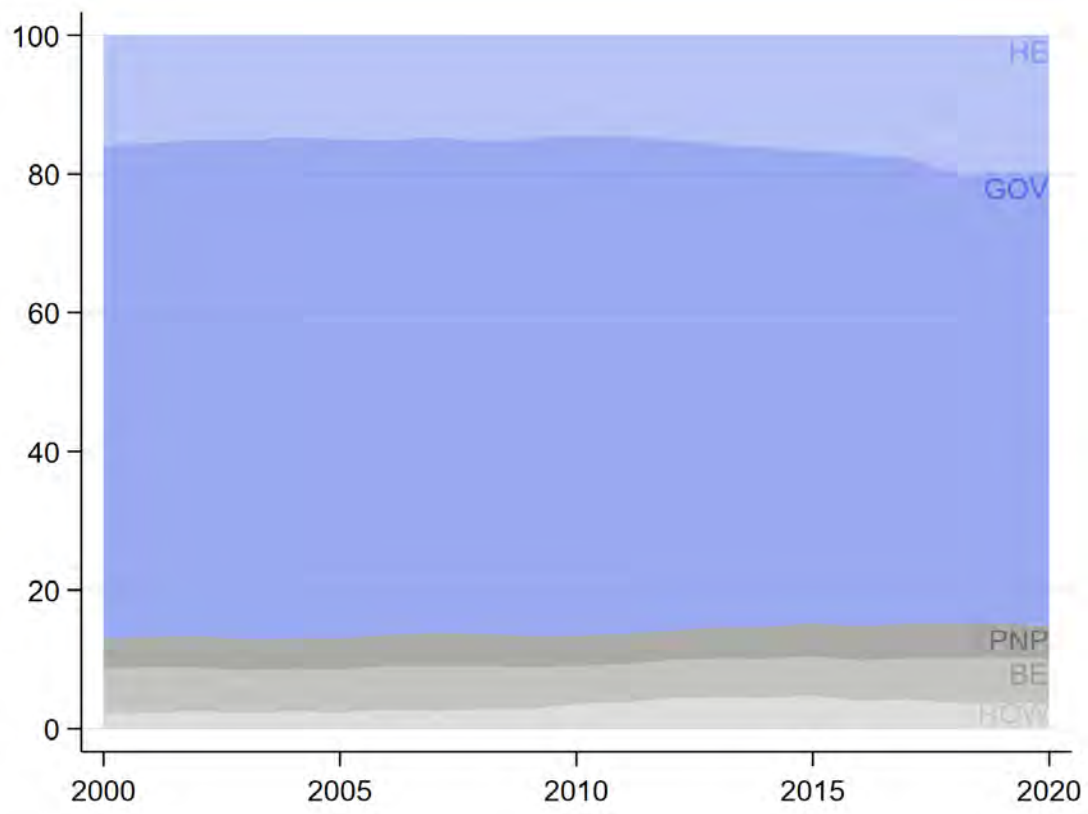
Table A.III: (continued)

φ	Description
0811	Crop and livestock production
0821	Forestry
0841	Veterinary
0911	Dental studies
0912	Medicine
0913	Nursing and midwifery
0914	Medical diagnostic and treatment technology
0915	Therapy and rehabilitation
0916	Pharmacy
0923	Social work and counselling
1011	Domestic services
1013	Hotel, restaurants and catering
1014	Sports
1015	Travel, tourism and leisure
1031	Military and defence

Note: This table shows the scientific fields Φ where universities contribute according to the UNESCO's ISCED-F 2013. This taxonomy considers 149 4-digit fields (only 3 levels as the first two digits concern the same *broad field* where 64 are residual fields for unknown affiliations (9999), not further defined (0000, 0110, 0210, 0220, 0230, 0300, 0310, 0320, 0400, 0410, 0500, 0510, 0520, 0530, 0540, 0700, 0710, 0720, 0730, 0800, 0810, 0900, 0910, 0920, 1000, 1010, 1020, 1030), not elsewhere classified (0099, 0119, 0229, 0239, 0299, 0319, 0329, 0399, 0419, 0499, 0519, 0529, 0539, 0599, 0619, 0719, 0729, 0799, 0819, 0899, 0929, 0999, 1019, 1029, 1039), interdisciplinary (0188, 0288, 0388, 0488, 0588, 0688, 0788, 0888, 0988, 1088) and 26 are valid fields not considered by the FSO because those disciplines do not exist at UNI or UAS or because they are not prominent enough (0011, 0021, 0031, 0112, 0411, 0414, 0415, 0416, 0417, 0512, 0522, 0542, 0611, 0612, 0723, 0724, 0812, 0831, 0917, 0921, 0922, 1012, 1021, 1022, 1032, 1041). Of the remaining 59, 5 are residual categories considered by the FSO (0200, 0610, 0219, 0919, 1099) which I distribute over the fields in the same cluster based on each university's employment distribution in those clusters. The remaining 54 are listed above.

Higher education expenditure on R&D (HERD)

Figure A.I: Higher education expenditure on R&D (HERD), by source of funds, OECD



Source: OECD (2024a, 2024b), author's own calculations
Note: This figure shows the composition of the HERD by the source of funds within the OECD. The sources are either the higher education sector (HE), the government (GOV), private non-profit firms (PNP), business enterprises (BE), or the rest of the world (ROW).

A.II Data

A.II.i Surveys

Forms of Knowledge Transfers

Table A.IV: Forms and their categorization

Form	Mission	Creator
• Informal information exchanges with academic personnel	3^{rd}	U
• Attendance at conferences, exhibitions, workshops at universities	2^{nd}	U
• Reading and citing of academic publications	2^{nd}	U
• Joint laboratories	3^{rd}	B
• Use of universities' technical infrastructure	3^{rd}	B
• Employment of university graduates in R&D	1^{st}	U
• Contact of graduates with laboratories of their alma mater	3^{rd}	U
• Participation of students in R&D projects of the firm	3^{rd}	U
• Theses in cooperation with universities	3^{rd}	U
• Dissertations in cooperation with universities	3^{rd}	U
• Cooperation of academic scientists in R&D projects of the firm	3^{rd}	U
• Joint seminars	3^{rd}	B
• Teaching assignment of firm employees at universities	3^{rd}	F
• Attending continuing education courses at universities	1^{st}	U
• Research projects in cooperation with universities	3^{rd}	B
• Research contracts with universities	3^{rd}	U
• Research consortia with at least one participation from a university	3^{rd}	B
• Expert opinions from universities	3^{rd}	U
• Consulting services by the universities	3^{rd}	U

Note: This table contains the forms of knowledge flows I count as transfers. The first column contains the detailed description of the form as used in the SKTS. The second column classifies them along the universities' traditional missions of education (1^{st}) and research (2^{nd}) as well as its modern mission of an active contribution to society (3^{rd}). The third column classifies them along the creator of the knowledge being transferred, where U signals universities, F signals firms, and B signals both.

Technologies

Table A.V: Technologies $\mathcal{X}$

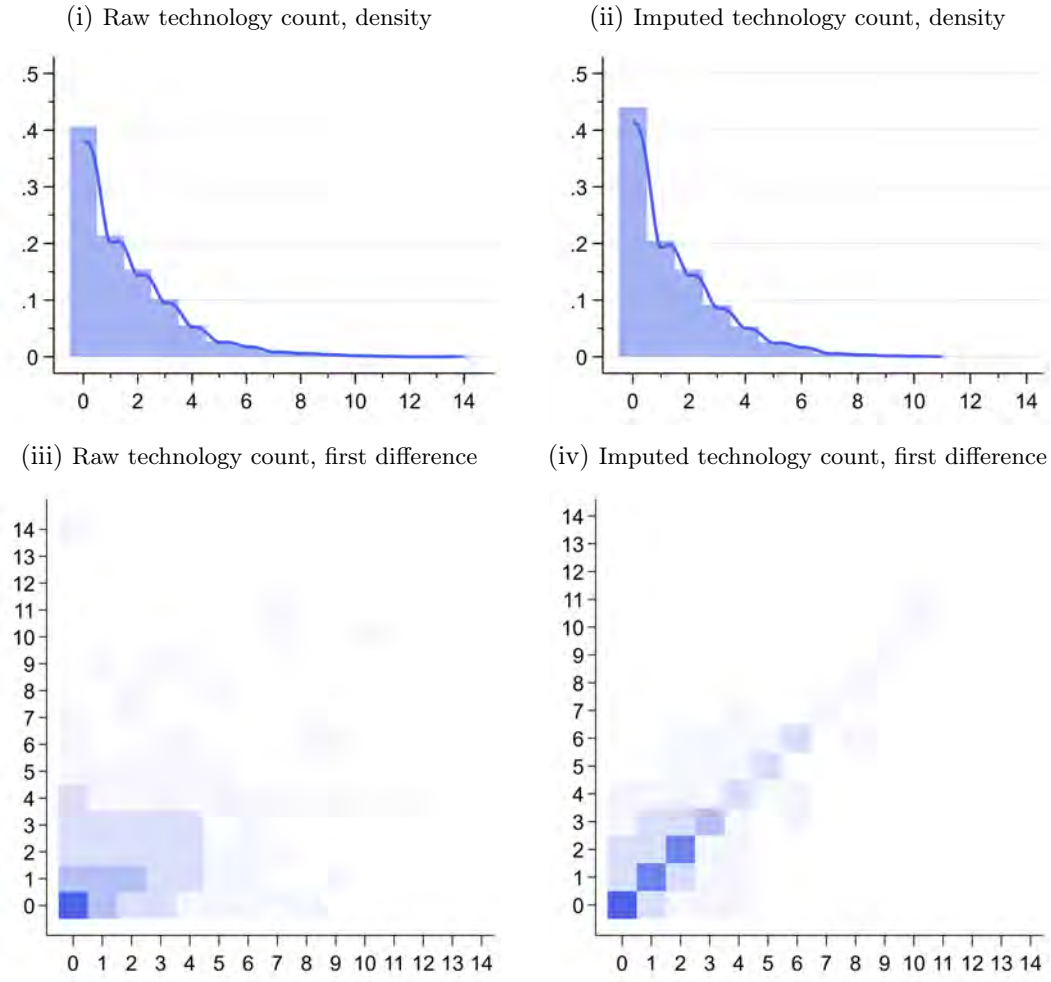
χ	Description
1	Nanotechnology
2	New Materials
3	Microelectronics and Semiconductor Technology
4	Laser Technology, Optoelectronics, Displays
5	Computer science
6	Telecommunications and Information Technology
7	Biotechnology and Genetic Engineering
8	Medical and Health Technology
9	Manufacturing engineering
10	Transport, Traffic Engineering, Logistics
11	Energy Technologies
12	Environmental and Resource-Saving Technologies
13	Geoscientific Technologies
14	Financial Modelling

Note: This table shows the 14 technologies $\mathcal{X}$ where firms contribute as considered by the SKTS and SIDS. While this list covers the most important categories of Swiss innovations, it lacks many features of a taxonomy like exhaustive coverage, equal-sized partition, broad expert consensus, or common usage. Compared to industrial taxonomies, it is advantageous in being a more granular measure and allowing for multiple affiliations per firm.

As mentioned in section 3.2.3, the first wave of the SKTS lacks information on technologies. Additionally, 169 of the 3489 observations from the second and third wave lack this information. Since I rely on this information to construct the technological exposure, I impute those values. Before the imputation, I correct unreliable information.

The underlying assumption behind those corrections is that a firm's contributions to technological fields are narrow and fairly stable over time. Figure A.II shows the distribution of the number

Figure A.II: Technology count before and after imputation



Note: This figure shows the distribution of the technology counts d_{it}. Subfigure i and ii show the density before and after imputation. The horizontal axis measures the count and the vertical axis the fraction. Subfigure iii and iv show the distribution of the first difference Δd_{it} before and after imputation. The horizontal axis measures d_{it} and the vertical d_{it-1}. Cells measure relative frequencies of that cell in the total matrix. Non-colored cells signal a probability of 0%, signal between 0% and 1%, between 1% and 5%, between 5% and 10%, between 10% and 20%, and signal above 20%.

of fields $d_{it} = \sum_{\chi \in \mathcal{X}} d_{it\chi}$ where a firm contributed to in the last three years prior to the survey. Subfigure iii shows the distribution of the first difference of this count $\Delta d_{it} = d_{it} - d_{it-1}$. Outlined in table A.V, each technology covers a broad range and they are sufficiently distinct from each other such that it is nonsensical if those first differences are large. If a firm contributes to all 14 technologies in one period but to none in the 6 years before that, it is evidently misreported. Specifically, I use to rules to adjust technologies

Rule 1: If $\Delta d_{it} \geq 5$, use the intersection $\mathcal{D}_{it} \cap \mathcal{D}_{it-1}$

Rule 2: If $5 > \Delta d_{it} \geq 3$ and $d_{it} \geq 2 * d_{-it}$, use the intersection $\mathcal{D}_{it} \cap \mathcal{D}_{it-1}$

where $\bar{d}_{-it} = 1/(I_{c(it)} - 1) \sum_{js \neq it : c(js) = c(it)} d_{js}$ is the holdout average number of technologies of the NACE class (4 digit) $c(it)$ observation (it) belongs to, $I_{c(it)} = |\{js : c(js) = c(it)\}|$ is the number of observations in that class, and $\mathcal{D}_{it} = \{d_{it\chi}\}_{\chi}$. Both rules adjust that firm's technologies to the subset that is common in both periods. The first does so for all firms with a disparity of more than 5 technologies. The second for those with a disparity of 3 or 4 technologies and where the number of technologies reported is larger than twice the number of technologies within the same industry. Subfigure iv shows the distribution of first differences after that data cleaning (and the subsequent imputation). The outliers are gone and the frequencies are more centered around the diagonal with a strong gravity towards the bottom left corner. Subfigure i and ii show the densities of those counts before and after imputation and confirm the minimal impact of the imputation on the distribution beyond outlier corrections as well as the concentration of technologies at the bottom. Roughly 40% of all observations have no contributions, 20% contribute to exactly one technology, 15% contribute to 2, 10% to 3, and 15% to 5 or more technologies.

After cleaning technologies according to rules 1 and 2, I impute the 14 technologies for the 2700 observations with missing data. First, I impute those values from information of the same firm and replace the missing values with $d_{i\chi} = \max \mathcal{D}_{i\chi}$ which measures if firm i ever contributed to technology χ and $\mathcal{D}_{i\chi} = \{d_{it\chi}\}_{t \in \mathcal{T}_i}$ is the set of technology indicators of the firm for all its existing waves $\mathcal{T}_i$. Second, I use data of firms in the same cluster if the firm cannot impute itself. Clusters are technologically homogeneous within and heterogeneous between them. I build them from partitioning the sample according to 27 industries listed in table A.II, 3 size

Table A.VI: Imputation of technologies

	SKTS wave			
	1	2	3	Σ
Before imputation	2531	36	133	2700
After self imputation	1318	28	102	1448
After cluster imputation	0	0	0	0

Note: This table shows the number of observations that lack data on technologies at the start, after the first imputation, and after the final imputation. Of the 6020 observations, 55% have original data, 76% have data in some wave, and 100% have data after imputation from the same cluster.

groups, and 1 R&D indicator. Table A.VII shows the resulting 162 clusters and the number of firms with and without data on technologies. Most cells contain sufficient information for a meaningful imputation and the information size grows with the imputation size. One the cell of large firms from industry 5 without R&D has no information but firms in need of imputation. I assign this unique firm to industry 6 and leave all else unchanged. Within each cluster, I first compute the average technology indicator $\bar{d}_{c(it)\chi} = 1/(I_{c(it}-1)\sum_{js\neq it:c(js)=c(it)} d_{js\chi}$ where $c(it)$ is the cluster observation (it) belongs to. I then use technology specific thresholds $\chi_{c(it)}$ to dichotomize these averages such that the overall distribution remains unaffected. Specifically, I use $\vartheta_\chi = \bar{d}_\chi + .2(1-\bar{d}_\chi$. $\bar{d}_\chi = 1/IT\sum_{it} d_{it\chi}$ is the sample average of the technology indicator[46] and .2 is the parameter which best aligns the raw technology propensity with the imputed propensity. Within each cluster, I assign $d_{c(it)\chi} = \mathbb{1}\{\bar{d}_{c(it)\chi} \geq \vartheta_\chi\}$ to those firms that cannot impute themselves.

Table A.VI shows the success of the imputation. Of the 2700 observations that lack information on technologies, 54% impute themselves and 46% derive from their clusters propensity. A further check on the validity of the imputation comes from figure A.III. Subfigure i shows the propensity of technological contributions per NACE section (2 digit) before the imputation. Subfigure ii shows the same thing after the imputation. The patterns are fairly similar suggesting a valid imputation process.

[46]Note that $IT = \sum_i T_i = \sum_t I_t \neq I * T$ is the number of observations in the unbalanced sample where $T_i = |\mathcal{T}_i|$ is the number of waves where firm i participates and $I_t = |\mathcal{I}_t|$ is the number of firms participating in wave t

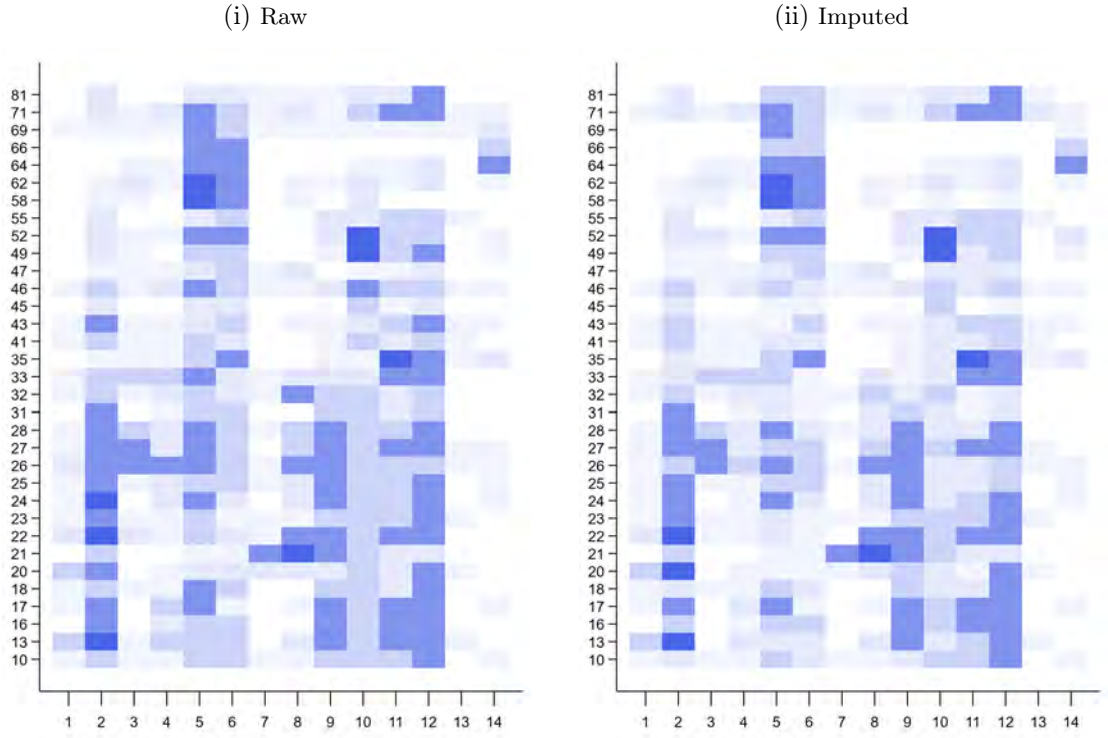
Table A.VII: Technology cluster composition and size

	Small		Medium		Large	
Industry	nRD	RD	nRD	RD	nRD	RD
1	60	21	47	47	14	3
2	19	10	11	13	1	5
3	57	11	22	21	3	10
4	31	4	41	8	8	4
5	24	15	23	31	0	10
6	29	39	8	34	2	16
7	5	7	4	24	1	14
8	25	13	16	11	3	7
9	12	3	16	16	6	9
10	152	39	79	74	7	17
11	78	76	38	91	7	45
12	26	22	13	27	3	33
13	65	52	35	138	4	52
14	9	2	1	8	2	10
15	59	13	34	20	7	6
16	45	10	14	9	6	3
17	48	7	32	11	13	10
18	79	2	85	13	33	8
19	152	7	73	15	16	4
20	151	21	106	29	52	12
21	127	3	108	12	51	13
22	18	15	20	11	9	5
23	25	9	10	12	4	9
24	123	3	25	9	50	26
25	69	10	35	14	11	11
26	108	26	47	32	2	10
27	70	3	55	5	22	9

Note: This table shows the composition of the clusters I use for the imputation of firms which cannot impute themselves. The 27 industries are those listed in table A.II, small, medium, and large firms are industry specific partitions, and nRD and RD signal absence and presence of R&D in the firm. Each cell contains the number of observations that have data on technologies. The shadings indicate the size of observations that require imputation. No shading implies no firms, between 1 and 9, between 10 and 19, between 20 and 49, and above 50 firms.

Start-of-period Variables As I mentioned in section 3.2.4, not all start-of-period values on the controls can be retrieved from the SKTS. Evident in figure 3-2, the first survey wave lacks a predecessor and we require a different data source to obtain values from 6 years prior. Additionally, firms partially respond to the surveys which reinforces the issue at hand. Luckily, the SIDS features the same questions, bases on the same sample (KEP) and is conducted by the

Figure A.III: Technology propensity before and after imputation, over industries



Note: This figure shows the propensity of technological contributions per NACE section (2 digit). The vertical axis measures NACE codes, the horizontal axis technologies. Each cell reports industry j's propensity to contribute to a given technology χ as $1/IT_j \sum_{it \in \mathcal{IT}_j} d_{it\chi}$ where $\mathcal{IT}_j$ is the set of observations that belong to industry j. Uncolored cells imply that 0% of observations in a given industry contribute to that technology, between 0% and 5%, between 5% and 10%, between 10% and 20%, between 20% and 50%, and above 50%. Subfigure i applies to data prior to imputation and ii to data after imputation. I only report sections where more than 30 observations have data on technologies before imputation.

same institute (KOF). I use both surveys to obtain the start-of-period values with the following procedure[47]

Step 1: Get the original values lagged by 6 years from the SKTS

Step 2: Get the original values lagged by 6 years from the SIDS

Step 3: Get the average original values lagged by 3 and 9 years from the SIDS

Step 4: Impute the values

[47]Throughout this section, I ignore the one year gap between wave 2 and 3 and treat everything as if it did not exist. That is solely out of convenience for the reader and has no implication on the results. I used the wave 2, wave 9 and finally waves 8 and 10 for steps 1, 2 and 3, respectively.

I use each subsequent step only if I cannot obtain the data via its predecessor. For example, if a firm in 2011 fails to participate or report that information in wave 1 of the SKTS, I search for that information on the same firm in wave 6 of the SIDS, as figure 3-2 shows. If that fails, I search for the information in wave 5 and 7. If that fails, I impute it as follows. First, I create growth factors of variable w_{it}^{ω} as $\dot{w}_{it}^{\omega} = w_{it}^{\omega}/w_{it-1}^{\omega}$ for all observations that have data after step 3. Second, I get rid of outliers below $Q_1 - 3 \times IQR$ and above $Q_3 + 3 \times IQR$, where Q_1 and Q_3 are the first and third quartile and $IQR = Q_3 - Q_1$. Furthermore, the imputations stem from per capita values, except for the R&D intensity which is expenses in relation to turnover, to avoid skewed distributions and heavy outliers. Third, I construct the first $\hat{\mu}_1(\dot{w}_s^{\omega})$ and second (central) moment $\hat{\mu}_2(\dot{w}_s^{\omega})$ of the empirical distribution for the three stratifying groups s comprising year, industries outlined in table A.II and size classes (small, medium, large). Fourth, I create random draws from a normal distribution with those empirical moments $\hat{\dot{w}}_{s,it}^{\omega} \sim \mathcal{N}(\hat{\mu}_1(\dot{w}_s^{\omega}), \hat{\mu}_2(\dot{w}_s^{\omega}))$ for those strata. Fifth, I take the average random draw across the year-industry-size triple the observation belongs to as $\hat{\dot{w}}_{it} = \sum_s \hat{\dot{w}}_{s,it}^{\omega}/3$. Sixth, I impute the missing value as the firm's current value divided by the inverse of that average random draw $\hat{w}_{it-1}^{\omega} = w_{it}^{\omega}/\hat{\dot{w}}_{it}$.

Table A.VIII shows how many observations fail to deliver information after step 2, 3, and 4. For 30% of observations from wave 1 I successfully obtain original data lagged by 6 years, either via the SKTS or SIDS. The same is true for 59% of observations from wave 2 and 46% of observations from wave 3. The difference between waves is due to a redrawn sample between wave wave 2 and wave 3 and due to the lack of predecessors of wave 1. Overall, 47% of all observations have original data lagged by 6 years. A further 16% have original data lagged 3 or 9 years from the SIDS. For the remaining 37%, I get data through the imputation process described above and obtain data for another 34%, such that only 3% are left without any information.

Table A.VIII: (Un)Availability of start-of-period variables

After Step 2

	SKTS wave 1	2	3	Σ
w^1_{it-1}	1102	495	825	2422
w^2_{it-1}	1159	565	847	2571
w^3_{it-1}	1737	549	864	3150
w^4_{it-1}	1760	563	862	3185
w^5_{it-1}	1231	639	863	2733
w^6_{it-1}	1510	732	912	3154
w^7_{it-1}	1510	732	912	3154

After Step 3

	SKTS wave 1	2	3	Σ
w^1_{it-1}	716	243	721	1680
w^2_{it-1}	750	283	732	1765
w^3_{it-1}	1002	270	740	2012
w^4_{it-1}	1020	290	744	2054
w^5_{it-1}	796	329	752	1877
w^6_{it-1}	984	397	799	2180
w^7_{it-1}	984	397	799	2180

After Step 4

	SKTS wave 1	2	3	Σ
w^1_{it-1}	0	0	1	1
w^2_{it-1}	0	0	1	1
w^3_{it-1}	1	4	0	5
w^4_{it-1}	1	0	0	1
w^5_{it-1}	19	1	8	28
w^6_{it-1}	90	33	78	201
w^7_{it-1}	90	33	78	201

Note: This table shows the number of observations that lack data on start-of-period variables after steps 2, 3, and 4. Of the 6020 observations, wave 1 records 2531, wave 2 1794, and wave 3 1695. 47% of those observations have original data lagged by 6 years, 63% have original data lagged 3, 6 or 9 years, and 3% have no data even after imputation.

A.II.ii Variables

Shocks This paragraph contains all information on the university laws (primary legislation enacted by the university sponsors), their derived bylaws (primary legislation enacted by the the university board), and their derived ordinances, directives, guidelines, and handbooks (secondary legislation enacted by the university executives, summarized as *regulations*) that incentivize academics to transfer their knowledge to industry. As mentioned in section 3.2.3, I focus on distribution keys from net returns of royalties since those are the most exogenous to firms and hence least likely affected by their actions. If the regulations are publicly available, I link them via the date they came into force. Otherwise, I obtained the documents from direct correspondence with university personnel, most often the head of the TTO. Those documents are available upon request after consultation with the legal services of the corresponding university. The correspondences were also invaluable to confirm the prior incentive structures and the motivations behind the enactments.

UGE (29.03.1998)

Directives en matière d'accords de transferts de technologies et de compétences

Inventor:	1/3
Unit:	1/3
University:	1/3

Background: Shortly before the inception of the TTO (Unitec) in 1999, a regulation came into force on the 29.03.1998 that governed knowledge transfers. On the 03.09.1999, this regulation was extended by distribution keys where 1/3 of the net returns of inventions accrue to the inventors, 1/3 to the affiliated unit, and 1/3 centrally to the university. The directive was lightly modified on the 01.10.2005 such that half of net revenues below CHF 50'000 accrue to the inventor and a quarter to the affiliated unit and the university while the old rule applies to any net revenues above CHF 50'000. Due to minor changes thereafter, I use the first regulation and since it is before my observation horizon, UGE does not record a regulation *change* and hence no shock.

UBA (01.01.2000)

Ordnung über Nebentätigkeiten, Vereinbarungen mit Dritten und die Verwertung von geistigem Eigentum im Rahmen der universitären Tätigkeit (441.200)

Background: On the 01.01.2000, the UBA introduced an ordinance on secondary employment and collaboration with third parties. Section 5 of that document concerned the establishment of a TTO and crucially the distribution keys that assigned 40% of net returns to the inventor, 30% to

Inventor	4/10
Unit	3/10
University	3/10

their unit, and 30% to the UBA. On the 23.09.2004, a revision of that ordinance (441.200) with a stronger focus on the exploitation of intellectual property was enacted that is still in force today. The keys remained unchanged but the university executives distribute cumulative net returns above CHF 1'000'000. In 2011, UBA joined UZH and UBE in their joint TTO (Unitectra). I use the first regulation as it already contains the distribution keys still in use today and other integral parts of future regulations.

UZH (22.12.2000)

Richtlinien zur wirtschaftlichen Verwertung von Forschungsergebnissen and der Universität Zürich

Inventor	1/3
Unit	1/3
University	1/3

Background: In 1999, the University of Zurich and the Univeristy of Bern (UBE) created a common TTO called Unitectra as a successor of a similar office called Biotectra focusing on technology transfer in life sciences of the UZH (since summer 1997) and UBE (since summer 1998). Since the 01.06.1998, a regulation was enacted to divided the first CH 50'000 of net revenue *per year* equally among the inventor and the unit. Amounts between CHF 50'000 and CHF 500'000 were split in three among the inventor, the unit, and the UZH, and amounts above CHF 500'000 annually were distributed by the university executives. On the 22.12.2000, the UZH revised their regulation and introduced new royalty keys. The first CHF 5'000 of gross revenue went to the unit, cumulative net revenues up to CHF 1'000'000 were split equally among inventor, unit, and the UZH and for cumulative net revenues above CHF 1'000'000, the 2/3 accruing to unit and UZH was decided by the university executives. A slight revision on the 01.09.2003 adds that the exclusive use rights on software reside with the UZH, in line with §12 a. of the university law. That regulation was lightly revised on the 30.03.2006 and the main changes included that the first CHF 5'000 of royalties from licenses do not go to the unit and that explicit rules were stated for biological materials and know-how. On the 01.07.2013 those regulations were merged with the revised financial handbook (FHB-UZH). Next to those rules, the FHB also includes a section on participation in firms, services like contract research, and secondary employments that also incentivize knowledge transfers. With the revision of the FHB on the 01.06.2021, an implementation regulation (ARF-UZH) was launched on the 21.01.2021 where the inventors receive 1/3 of the first cumulative net revenues below CHF 3'000'000, 1/4

of those above CHF 3'000'000 but below CHF 10'000'000, and 1/10 above CHF 10'000'000, the unit receives 1/3 of the net revenues but annual amounts above CHF 333'333 are governed by the university executives, and the rest accrues to the UZH. I use the 2000 regulation since it established the trisection that was the core of all future distribution rules.

UBE (01.01.2002)

Richtlinien der Universitätsleitung zur wirtschaftlichen Verwertung von immateriellen Arbeitsergebnissen der Universität Bern

Inventor	20/100
Unit	55/100
University	25/100

Background: Since 1998, the UBE is part of a joint TTO with the UZH. At least since the 22.10.2000, distribution keys were published on its website that assigned 20% to the inventors, 55% to the unit, and 25% to the UBE. At the same time, the bylaw on the university (UniV) stated in Art. 107d Abs. 3 that the university executives govern the distribution since the 01.01.2002. On the 27.10.2009, an official regulation that derived from the UniV came into force which stated the same distribution keys and modified ones for biological materials, know-how, and software (no direct revenues to the inventor but 75% to the unit). Additionally, it also covered ownership on IPR, some contracts with third parties, and start-ups. That regulation was abrogated on the 01.01.2014 and superseded with a mostly unchanged version except for drastically new keys. The first annual returns up to CHF 5'000 go directly to the unit, net revenues up to CHF 1'000'000 are split equally among inventor (+13pp), unit (-21pp), and university (+8pp) and for amounts surpassing that, the university executives decide how to distribute the 2/3 to unit and university. The keys for biological material, know-how, and software were adjusted to 2/3 (-8pp) for the unit and 1/3 (+8pp) to the UBE. That harmonized the distribution of revenues between the UZH and the UBE, while the UBA, that joined the Unitectra in 2011, has distinct keys. I obtained the 2009 document from the legal services which confirmed the absence of a prior written regulation. Despite the lack of a prior regulation, the same keys were published on the Unitectra website and its other founding member, the UZH, also published regulations around the same time. It is highly likely that UBE delegated the distribution of revenues to its TTO since its foundation and that the first regulation in 2009 was de facto inconsequential. I thus use the entry into force of the UniV Art. 107d as the relevant regulation change since the Unitectra website lacks a definitive inception date of those distribution keys.

HES-SO (20.02.2004)

Règlement sur la valorisation des connaissances acquises par la recherche au sein de la HES-SO et de la HES-S2

Inventor	1/3
Unit	1/3
University	1/3

Background: The regulation from the 20.02.2004 is not publicly available and I obtained it from their legal services. Next to a small section on participation in legal entities, this regulation states who owns an invention or an original work and establishes the trisection among inventor, unit, and university of net revenues. The legal services also confirmed that there was a small partial revision on the 20.07.2004 and that the complete revision on the 01.01.2015 was due to an organizational change while the content of the regulation remained unchanged. Similar to the ETH domain, most UAS are umbrella organizations comprising of multiple semi-independent institutes. In fact, the federal law on the universities of applied sciences (FHSG) enacted on the 06.10.1995 created the UAS as an association of prior existing schools sponsored by multiple cantons. The most extensive case is the HES-SO that spans 28 schools from 13 locations (Genève, Nyon, Lausanne, Yverdon-les-Bains, Sion, Sierre, Visp, Leukerbad, Fribourg, Neuchâtel, Le Locle, La Chaux-de-Fonds, Delémont) in 7 cantons (Genève, Vaud, Vallais, Fribourg, Neuchâtel, Bern, Jura). Very much in line with the IGBV-ETH, the regulations of the HES-SO allow each location to introduce their own regulations in accordance with those central rules. Since the questionnaire of the SKTS does not contain the single schools but only the UAS, I cannot use those granular regulations. Admittedly, they would be optimal as they raise the number of shocks and make the true spatial exposure of firms more credible.

PSI (26.02.2004)

Handhabung von Forschungs-, Dienstleistungs und Technologietransferverpflichtungen gegenüber Dritten (AW-90-00-08)

Inventor	1/3
Unit	1/3
University	1/3

Background: Mirroring the EMPA, the regulations of the PSI are not publicly available and only accessible through their intranet. I obtained the regulations directly from the head of industrial relations and its TTO. Sadly, their first regulation enacted on the 21.02.2001 (AW-90-00-08) was not retrievable, however its first revision on 26.02.2004 and the complete revision on the 25.11.2015 (AW-11-15-01). As in line with the EMPA, knowledge transfers are a core mission of the PSI and explicitly stated in those regulations. Their distribution keys also

assign 1/3 to inventors, their units, and the PSI unless the net returns of an inventor surpasses CHF 100'000 in which case the amount is assigned to the unit. Next to those rules, the regulations contain all contractual agreements that emerge with knowledge transfers. They emerged since the 1986 Federal Technology Transfer Act (FTTA) and include cooperative research agreements (CRADAs), contracts on research services like contract research or consulting, material transfer agreements (MTAs), confidentiality agreements like non-disclosure agreements (NDAs), confidential disclosure agreements (CDAs), or secrecy agreements, letter of intents (LoIs) or memorandum of understandings (MoUs), licensing or transfer of intellectual property rights (IPRs) or options on them, rules on entrepreneurship like rules on equity, preferential access to IPR or incubation, and finally rules on personnel transfers. This is the most comprehensive list on knowledge transfer contracts and covers all forms outlined in table A.IV. As mentioned in section 3.2.3, while all of them undoubtedly shape the incentive structure for knowledge transfers, I focus on distribution keys since they are most common across universities and least likely the target of interest of firms. Since the content of the first and complete revision do not differ significantly, I use the former. However, I cannot rule out that the same applies to the first enactment and its first revision. The falsification checks in section 5.1 address that concern.

EMPA (01.01.2005)

Erfindungen, Know-how und Patentanmeldungen (RHB-1.7.)

Inventor	1/3
Unit	1/3
University	1/3

Background: The rule handbooks (Regelhandbuch, RHB) are not publicly available and I obtained them directly from the head of EMPA's legal services and its TTO. On the 01.03.2000, the EMPA launched its first regulation (RHB-1.7) on inventions, know-how and patents. Although it did lay the foundation for future rules, it did not contain distribution keys and was rudimentary compared to succeeding versions. On the 01.07.2004, the ETH domain put a new framework on intellectual property rights into force called IGBV-ETH that harmonized the rules on intellectual property and academic entrepreneurship. Although that bylaw affected the ETHZ, EPFL, PSI, EAWAG, EMPA, and WSL, all six institutions enacted their own regulations at different times. Furthermore, the head of ETH transfer confirmed in a private conversation that the each institute had its own governance on the process and the central framework was of minor importance for their enactment. In the wake of that change, the EMPA enacted a revised and extended regulation on the 01.01.2005. Simultaneously, they created their TTO called Wissensnsmanagement und Technologietransfer (WMTT). The new regulation explicitly stated the division of net revenues where 1/3 accrued to the inventor, 1/3 to the unit, and 1/3 to the EMPA. In line with Art. 36 of the ETH law, the regulation also includes copyrights. They require special consideration,

since Art. 9 of the Federal Act on Copyright and Related Rights (CopA) declares that authors have exclusive rights to their works. Since copyrights include computer code (software), most regulations have special rules on software. Almost always, ownership resides with the author but the university get exclusive use rights on software as is the case in the revised EMPA regulation. In 19.11.2013, the MHB-4.3.1 replaced the RHB-1.7. and capped the cummulative returns at CHF 500'000 per inventor and at CHF 5'000'000 for the unit. Finally, a slightly revised version came into force on the 01.04.2021 without any major changes. I use the 2005 regulation as shock, since it is the first to explicitly state keys, extensively covers knowledge transfer incentives, and concurred with the establishment of the TTO. That decision is further backed by a private conversation with a member of EMPA's directorate who confirmed that the EMPA transformed from a testing to a research institute since 2003.

ETHZ (01.02.2005)

Richtlinien für die wirtschaftliche Verwertung von Forschungsergebnissen an der ETH Zürich

Inventor	1/3
Unit	1/3
University	1/3

Background: Due to its focus on technical disciplines like engineering and natural sciences, its national and international reputation, and its size, the ETHZ is the pioneer on knowledge transfers. On the 20.01.1988, they enacted regulations on research contracts (440.31) and on the 22.11.1994 (SLB 2211003-94) they enacted regulations on inventions, know-how, and patents. The latter contained distribution keys where 1/5 of net revenues accrued to the government, 4/15 to the inventor, 4/15 to the unit, and 4/15 to the ETHZ. On the 01.07.2003, regulations on the commercial exploitation of research results (440.4) superseded them and the keys were adjusted to an equal trisection of net revenues among inventors, units, and the ETHZ. Also on the 01.07.2003, new regulations on research contracts superseded the old ones. In line with the PSI, those contain an extensive list of collaborative research, contract research, consulting, MTAs, CDAs, NDAs, LoIs, MoUs, licenses, transfers, and options on IPR, sponsoring and donations, as well as contracts with national and international funding agencies. With the harmonization of the ETH domain brought about by the IGBV-ETH on the 01.07.2004, the ETHZ enacted a new exploitation regulation on the 01.02.2005. Due to the swift cascade of those regulations, their content is nearly identical. On the 01.05.2014 a revised document superseded that regulation and contained slightly modified rulings on decision agencies and extensions on equity stakes, open source software, and other intellectual property like trademarks, designs, materials, samples, prototypes and data. On the 01.01.2016, a revised regulation on research contracts superseded the old one. Finally, since the 1990s, ETHZ also supports academic entrepreneurs via ETH transfer and governed by guidelines on spin-offs enacted on the 12.07.1994 (SLB 1207003-94)) that were

replaced on the 01.12.2019 (440.5), and revised on the 01.01.2023 and regulations on equity stakes (440) that came into force on the 01.01.2015. I obtained all documents prior to the century break directly from the head of the ETH transfer. In a bilateral talk, he also gave invaluable insights into the reasoning behind those regulations. While the change on the 01.02.2005 left the content unchanged, it is still the most important date to consider. First, it is the direct implementation of the ETHZ of the IBGV-ETH but more important, the head of ETH transfer confirmed that this also concurred with a substantial reorganization of the ETH strategy to knowledge transfers. Despite its inconspicuousness, I thus use this regulation as the shock.

FHNW (01.01.2007)

Gesamtarbeitsvertrag (GAV) für die Fachhochschule Nordwestschweiz FHNW

Inventor	1/3
Unit & University	2/3

Background: As noted in the background on the HES-SO, the FHNW also comprises 9 schools from 4 locations (Brugg-Windisch, Olten, Solothurn, Basel) in 3 cantons (Aargau, Solothurn, Basel-Stadt). Their incentive structure on knowledge transfers are peculiar among Swiss universities. Everything is ruled in a collective labor agreement (Gesamtarbeitsvertrag, GAV) negotiated between the FHNW and 7 teachers and civil servants unions. The first came into force on the 01.01.2007 and lightly revised on the 01.01.2008, 01.01.2011, and 01.01.2020. Art. 9ff contain all rules on intellectual property, disclosure obligations, exploitation schemes, and distribution keys. 1/3 of all net revenues accrue to the inventor and the remaining 2/3 accrue to the FHNW that distributes them among the concerned units and the university. On the 26.05.2014, they introduced a regulation on spin-offs derived from the GAV. In direct correspondence, the head of their TTO (fitt.ch) confirmed that no other regulations besides those two existed and that he was also not aware of any disclosed rules prior to 2007. The secretary general confirmed this fact and also sent me the spin-off regulation. Hence I use the first regulation change.

EPFL (01.03.2007)

Directives de l'EPFL sur les contrats de recherche et le transfert de technologies (DCRTT)

Inventor	1/3
Unit	1/3
University	1/3

Background: Similar to the ETHZ, the EPFL is a Swiss knowledge transfer pioneer. In 1991, the EPFL founded their Science Park Foundation (PSE) in 1991 that promoted innovation through technology transfer and start-ups which evolved into the EPFL Innovation Park (EIP) in 2014. Simultaneously, they established an office for industrial relations (SRI) that evolved into their TTO in 2011. It supports the exploitation of research, research contracts, as well as academic entrepreneurs via the EIP. Predating the office, the EPFL enacted regulations on research contracts on the 20.01.1988. At least since the 08.04.2001, they also had distribution keys published on their website but not in an official regulation. In line with the introduction of the IGBV-ETH (see EMPA), the EPFL officially launched a regulation on research contracts and technology transfer (DCRTT) on the 01.03.2007 that abrogated the prior regulation on research contracts as well as Art. 7.1 to 7.4 of the financial regulations that came into force on the 01.01.2002 (LEX 5.1.1). The DCRTT was lightly revised on the 01.07.2009. On the 27.05.2013, a new extended regulation that covered sponsoring, reporting obligations, and signing agency (DSCRTT, LEX 3.4.1) superseded the DCRTT, and lightly revised versions came into force on the 01.09.2013, the 01.01.2017, the 27.03.2017, the 23.04.2019, and the 25.01.2021. Since its inception, those regulations contained an equal trisection among inventor, unit, and EPFL. Predating that, these keys likely existed since the inception of the SRI in 1991 as they were declared on its homepage at least since the 08.04.2001. I retained all documents that are not linked above directly from the head of the TTO except for those predating the century break. In concordance with the ETHZ, I use the first regulation after the IGBV-ETH came into force which is also reasonable since prior to that date, no comprehensive regulation on knowledge transfer existed beyond some preliminary rules on research contracts.

BFH (01.01.2009)

Weisung über den Wissens- und Technologietransfer an der Berner Fachhochschule

Inventor	1/3
Unit	1/3
University	1/3

Background: The BFH comprises 8 schools from 4 locations (Bern, Burgdorf, Biel, and since 2023 Basel) in 2 cantons (Bern, Basel-Stadt). On the 01.01.2009, the BFH enacted a comprehensive regulation on knowledge transfers including protection of intellectual property, their exploitation, and contracts related to research. A lightly revised version came into force on the 29.06.2017 and finally on the 01.01.2023. Since its inception, the equal trisection of revenues between inventor, unit, and BFH was clearly established. I obtained all documents directly form the vice rectorate for research and the legal services. They also confirmed that the launch in 2009 was the first unified regulation on knowledge transfer and hence I use them as shock.

UL (01.03.2009)

Règlement sur la valorisation des résultats de recherche au sein de l'Université de Lausanne et des Hospices cantonaux (414.11.2)

Inventor	1/3
Unit	1/3
University	1/3

Background: In February 2000, UL and the associated university hospital (CHUV) founded a joint TTO (PACTT). A rudimentary regulation on research contracts came into force on 01.09.2000 but it did not contain any distribution keys nor a comprehensive coverage of contracts. On the 01.03.2009, the canton of Vaud enacted an exploitation regulation (RVRR, 414.11.2) for research conducted at UL and CHUV that ruled an equal trisection of revenues among inventors, units, and the university. In the same vein, both institutes introduced a comprehensive regulation on knowledge transfers including intellectual property rights, their exploitation via transfer or start-ups, and distribution of revenues that came into force on the 01.01.2010. Since keys are only part of the RVRR, I use that date as shock.

HSG (03.05.2010)

Richtlinien für Nebenaktivitäten und den Nebenerwerb von Dozierenden an der HSG (III.B.1.08)

Inventor	NA
Unit	NA
University	NA

Background: Due to its lack of technical faculties and strong focus on social sciences, the HSG does not have a TTO nor any regulations that govern the commercial exploitation of research. What they have instead, is a strong focus on consulting and leadership through positions in boards of directors which is governed by regulations on secondary employment. On the 03.05.2010, they introduced such regulations (III.B.1.08) that were partially revised on the 01.11.2019. Since the content is mostly unchanged, I use the prior version as shock.

UNE (01.08.2012)

Règlement concernant la valorisation de la recherche (416.108)

Inventor	1/3
Unit	1/3
University	1/3

Background: At least since the 27.06.2007, UNE has a TTO. Although its inception is beyond my knowledge, the first exploitation regulation (416.108) came into force on the 01.08.2012. Since there is no abrogation stated within the document, it is the first of its kind. It also foresees an equal trisection of revenues among inventor, unit, and university while it allows the rectorate to limit the inventor shares to 10% for amounts surpassing CHF 3'000'000 and re-allocate the remainder among unit and UNE.

ZFH (01.10.2014)

Finanzreglement der Zürcher Hochschule für Angewandte Wissenschaften (1.04.01)

Inventor	1/5
Unit	2/5
Department	1/5
University	1/5

Background: The ZFH was founded with the entry into force of the law on the ZFH (414.11) on the 27.09.1998 as a central governing body over 10 individual schools and was headed by a counsel (FHR) that still acts as governing body today. On the 02.04.2007, a revised law on the ZFH (FaHG, 414.10) was launched that compressed the schools into 3 larger organizations (ZHAW, ZHdK, PHZH). In the same vein, they revised their personnel regulation (PVF, 414.112) on the 01.08.2008 that abrogated the older version that came into force on the 01.09.2000. They contain rules on secondary employment and intellectual property (§35 - §49 in the 2000 version, §27 - §42 in the 2008 version) but §47 leaves the distribution of revenues to the universities executives. On the 01.10.2014, the ZHAW enacted their first financial regulations (1.04.01) that covered equity stakes and intellectual property. Art. 9.2 contains distribution keys and is the implementation of §47 PVF. 20% of net revenues accrue to the inventor, 40% to the associated research unit, 20% to its department, and 20% to the ZHAW. Those keys are still in place today and had no antecedents. In 2022, the ZFH was dissolved and the three schools are individually accredited UAS (ZHAW, ZHdK, PHZH) since then while the ZHAW still remains the most relevant with respect to knowledge transfers.

Enactments after 31.12.2017

SUPSI (01.01.2018)

Regolamento SUPSI per la tutela della proprietà intellettuale

Inventor	1/3
Unit	2/9
Department	2/9
University	2/9

Background: The SUPSI introduced a comprehensive regulation on intellectual property on the 01.01.2018. On the 01.01.2020 they followed suit with a regulation on start-ups and spin-offs. Both regulations are beyond my observation horizon and thus not considered in this study.

USI (25.02.2019)

Direttiva sul trasferimento tecnologie e del sapere

Inventor	1/3
Unit	1/3
University	1/3

Background: I obtained the document directly from the head of the TTO (USI Transfer). He confirmed that there were no prior regulations and that on the 25.02.2019 they introduced a comprehensive regulation on knowledge transfers that covers protection of intellectual property, its commercialization via transfer or spin-offs, and a comprehensive ruling on contracts related to knowledge transfers. Like its neighbouring UAS, the regulation postdates the observation horizon.

Enactments before 31.12.2017, but unclear when

UFR (28.08.2012)

Richtlinien zu Erfindungen, dem Schutz des geistigen Eigentums, Patenten und gewerblichen Beziehungen im Forschungsbereich (135.100)

Inventor	1/3
Unit	1/3
University	1/3

Background: On the 28.08.2012, UFR introduced a comprehensive regulation on knowledge transfers (135.100). Simultaneously, they created a TTO (tt-fr) to support them, the Adolphe Merkle Institute, the Haute école d'ingénierie et d'architecture (HEIA-FR), and the Haute école de gestion Fribourg (HEG-FR) that are both part of the HES-SO and which relocated their

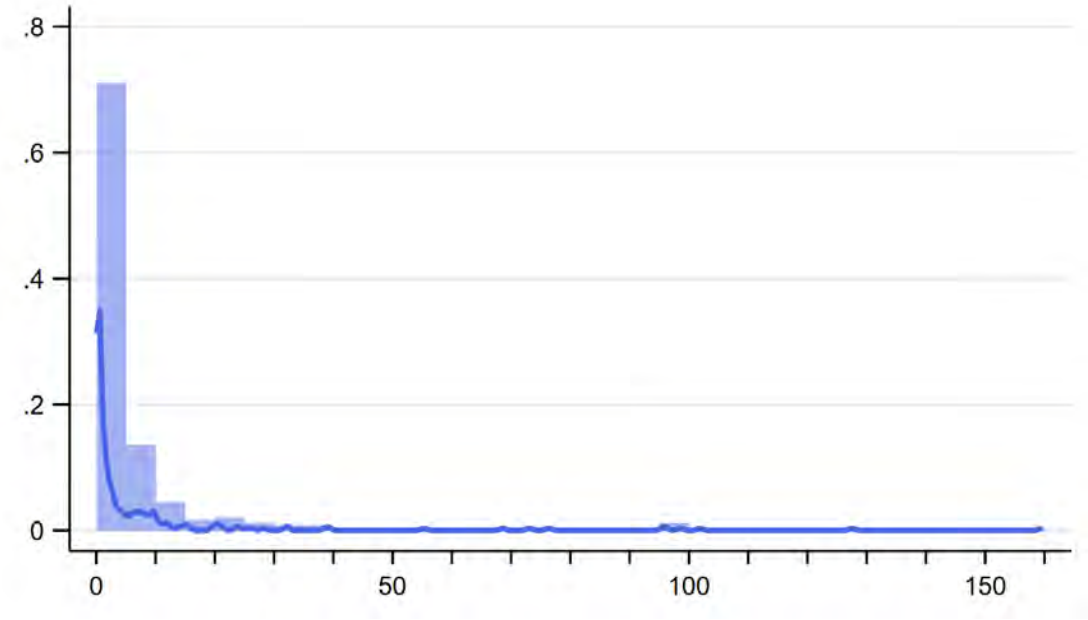
web presence to LinkedIn in 2022 while the UFR integrated them into a more comprehensive unit on knowledge transfer at the same time. TTO. That regulation contains a clear equal trisection of revenues among inventor, unit, and UFR. The only problem is that it was predated by an instruction sheet on inventions, patents, and certain contracts that came into force on the 11.04.2001. That regulation is not retrievable from the web archive nor could the TTO or the legal services provide the document. This is problematic as it allows the probability that those keys existed prior to 2012 and even that some regulations existed prior to 2001. I opt ot treat UFR as if they never had a regulation *change* and alleviate doubts about that assumption in section 5.1 but the fact that they focus primarily on social sciences and humanities render them a minor player in knowledge transfers and likely irrelevant for this study.

No enactments yet The two institutes EAWAG and WSL affiliated with the ETH domain have no regulations that incentivize knowledge transfer. The head EMPA's TTO confirmed that they joined forces with the co-located EAWAG on the 01.01.2011 but both institutions have separate regulations, or rather that the EAWAG lacks them. Their research focus on the environment (forest and snow for WSL and water for EAWAG) explains the absence of such regulations rather well: their mission is not to conduct research with a high commercial potential. Similarly, the ULU focuses mainly on humanities and social sciences and thus lacks any regulations. The remaining two UAS, the HSLU and the FHO also do not have any regulations despite the presence of technical sciences. Like most UAS, the HSLU focuses primarily on (further) education which might explain the absence of such regulations. The FHO, which separated into the FHGR (accredited on the 21.06.2018) and the OST (accredited on the 16.12.2022) also lacks such regulations which was confirmed by their general secretary.

Exposures

Spatial exposure

Figure A.IV: Relocation distances of movers



Note: This figure shows the histogram of the farthest relocation distance for the 243 firms that move at least once between 1999 and 2018. The line is the kernel density estimate using a bandwidth of .4, i.e. 400 meters, and an Epanechnikov kernel. The horizontal axis measures the geodesic between the two locations in kilometers.

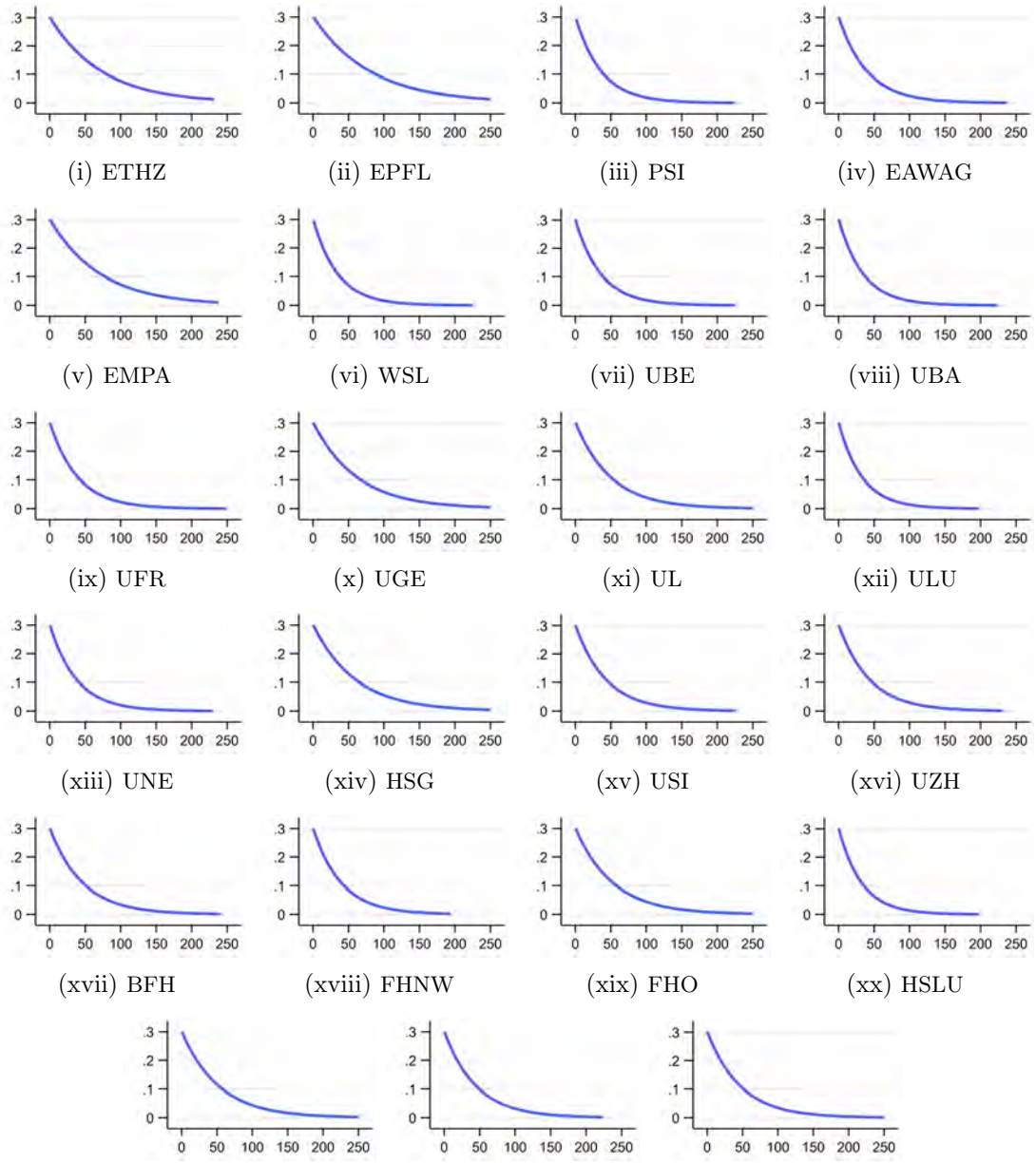
Technological exposure

Table A.IX: Estimates of intercept and slope from spatial exposure functions

	$\hat{\iota}_n$	$\hat{\delta}_n$
ETHZ	0.185	-0.014
EPFL	0.161	-0.013
PSI	0.034	-0.028
EAWAG	0.029	-0.025
EMPA	0.116	-0.014
WSL	0.013	-0.029
UBE	0.085	-0.028
UBA	0.074	-0.029
UFR	0.056	-0.026
UGE	0.044	-0.016
UL	0.025	-0.020
ULU	0.111	-0.031
UNE	0.035	-0.027
HSG	0.139	-0.017
USI	0.031	-0.023
UZH	0.063	-0.023
BFH	0.180	-0.022
FHNW	0.245	-0.026
FHO	**0.302**	-0.019
HSLU	0.241	-0.031
HES-SO	0.165	-0.019
SUPSI	0.114	-0.022
ZFH	0.155	-0.022

Note: This table shows the estimates of the university-specific spatial intercepts $\hat{\iota}_n$ and slopes $\hat{\delta}_n$ via maximum likelihood of the models described in 3.2.3. The estimates only rely on pre-regulation periods or the first survey wave if the university put the regulation into force before the 31.12.2002. The spatial decline parameters are exactly in the range of -10e-3 and -50e-3 suggested and recently used in the literature, e.g. Zheng and Kahn (2013) or Ahlfeldt and Feddersen (2018).

Figure A.V: Estimated spatial exposure functions per university



Note: This figure shows the spatial exposure per university assuming $\hat{\imath} = max\{\hat{\imath}_n\}_n$ and $\hat{\delta}_n$ from table A.IX and the functional form $\hat{\imath} * e^{\hat{\delta}_n p_{itn}}$. The vertical axis measures the predicted share of firms that receive knowledge form the university via transfers and the horizontal axis measures the geodesic between the university and the firm measured in kilometers.

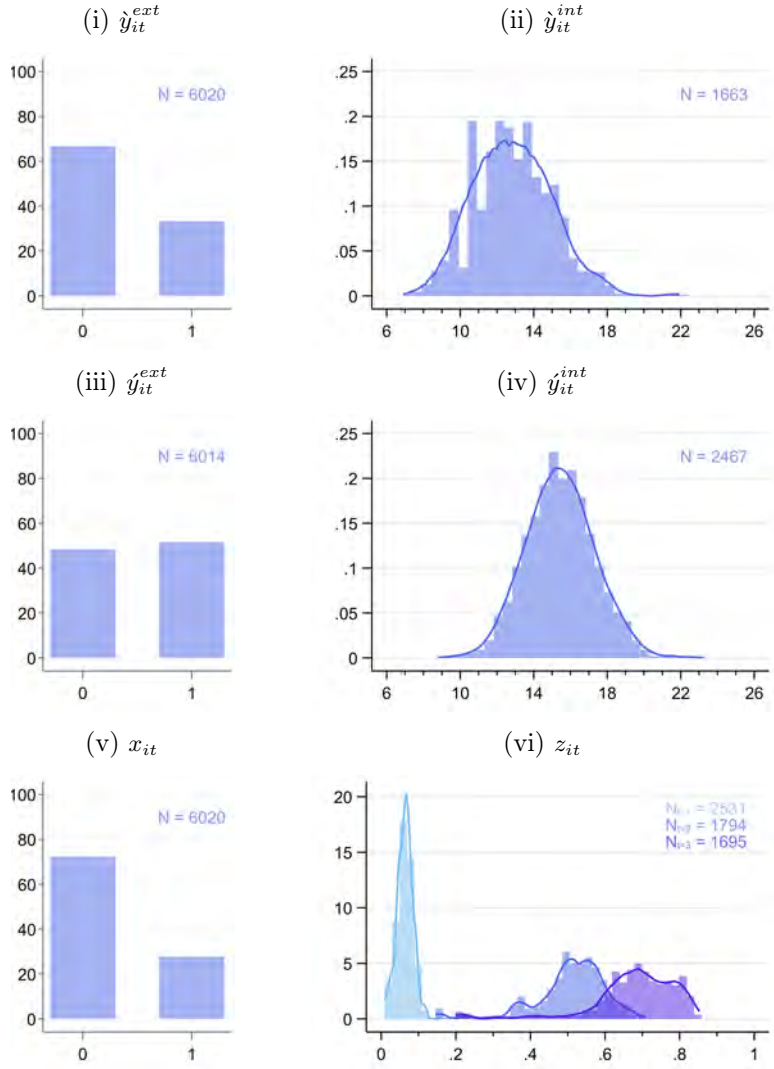
Summary graphs

Table A.X: Concordance between scientific fields Φ and technologies $\mathcal{X}$

φ \ χ	2	4	6	8	10	12	14
0311							✓
0412							✓
0511			✓				
0521						✓	
0531	✓		✓				
0532							
0533	✓	✓	✓				
0610			✓				
0613		✓					
0711	✓						
0712						✓	
0713							
0714	✓	✓	✓		✓		
0715				✓	✓		
0716					✓		
0721	✓						
0722	✓						
0731							
0732					✓		✓
0811							
0914				✓			
0916	✓						
0919				✓			

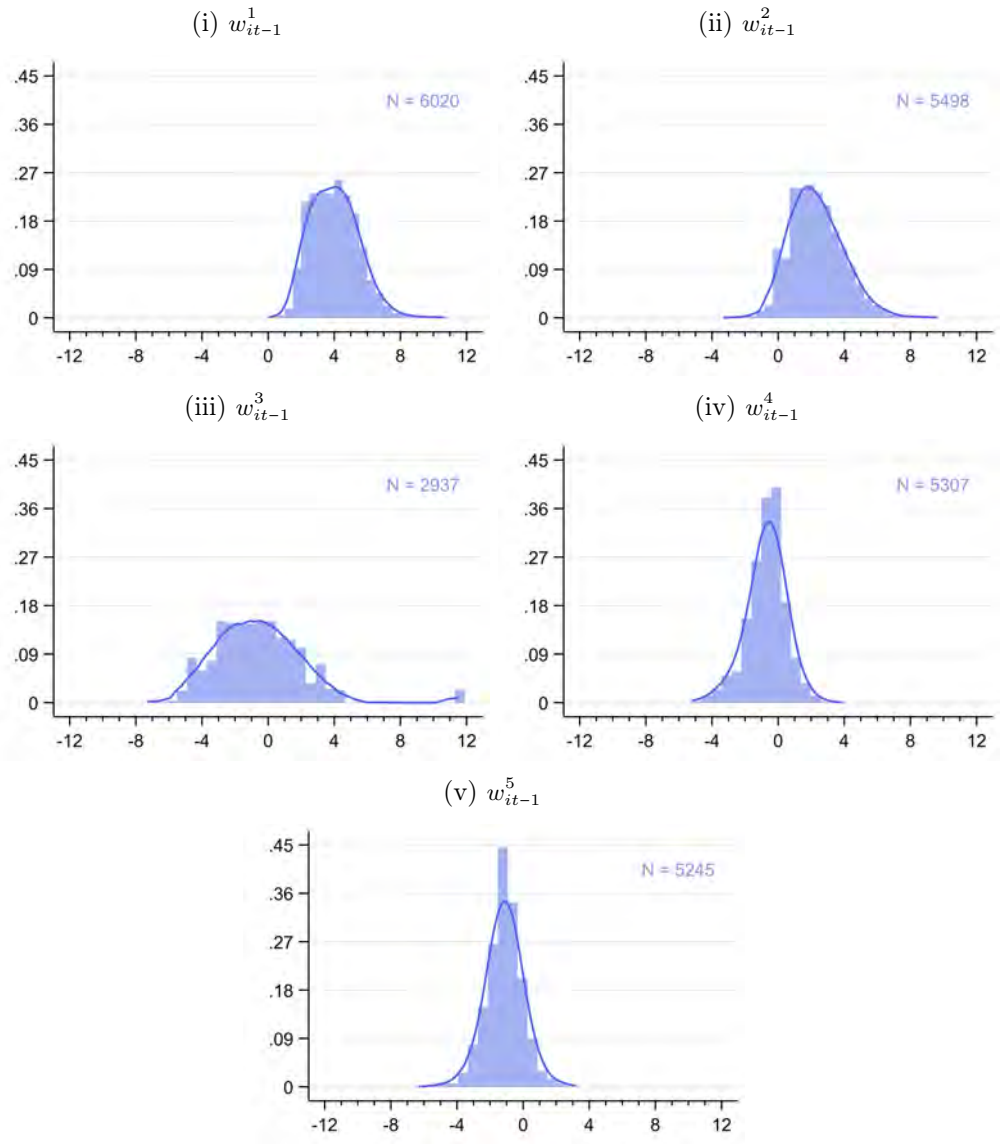
Note: This table shows the concordance between universities' scientific fields Φ and firm's technological activities $\mathcal{X}$. $c_{\chi\varphi}$ is 1 if the scientific field φ has its most useful application in technology χ and zero otherwise. The firms technologies stem from the SKTS and SIDS as outlined in table A.V. The universities scientific fields stem from the UNESCO's ISCED-F 2013. The sparse concordance links only 23 out of the 54 scientific fields listed in table A.III. This discrepancy comes from fields that do not produce innovation-relevant output and are hence ignorable for knowledge transfers (0111, 0113, 0114, 0211, 0212, 0213, 0214, 0215, 0221, 0222, 0223, 0231, 0232, 0312, 0313, 0314, 0321, 0322, 0413, 0421, 0541, 0821, 0841, 0911, 0912, 0913, 0915, 0923, 1011, 1013, 1014, 1015, 1031).

Figure A.VI: Summary statistics of the outcome variables



Note: This figure shows the summary statistics of the main variables. Subfigure i and ii show the extensive and intensive margin of innovation input $\grave{y}_{it}$. Subfigure iii and iv show the extensive and intensive margin of innovation output $\acute{y}_{it}$. Section 3.2.1 describes these outcome variables. Subfigure v shows the treatment variable $x_{it} = \mathbb{1}\{i \overset{t}{\leftarrow} \mathcal{N}\}$ described in section 3.2.2. Subfigure vi shows the shift-share instrument $z_{it} = \sum_n s_{itn} g_{nt}$ outlined in section 3.2.3 using g_{nt}^{shr} and assuming $\sigma = 2/3$. The extensive margins of the outcome and the treatment are binary measures and the plots are simple histograms where the vertical axis measures percentages. The intensive margin of the outcome and the instrument are continuous measures and the plots combine histograms and kernel density plots based on Epanechnikov kernels while the vertical axis measures densities. Due to the multimodal distribution of the instrument, I plot each wave with a different color highlighting the mechanical temporal trend. The corresponding sample sizes are marked in the top right corner.

Figure A.VII: Summary statistics of the control variables



Note: This figure shows the summary statistics of the control variables $\mathbf{w}_{it-1}$ outlined in section 3.2.4. All controls are continuous measures and the plots combine histograms and kernel density plots based on Epanechnikov kernels while the vertical axis measures densities. Only the intensive margin is depicted and subtracting the sample sizes marked in the top right corner from the total sample size of 6020 indicates how large the extensive margin is.

A.III Falsification

Table A.XI: The standardized effect of university knowledge transfers on firm innovation

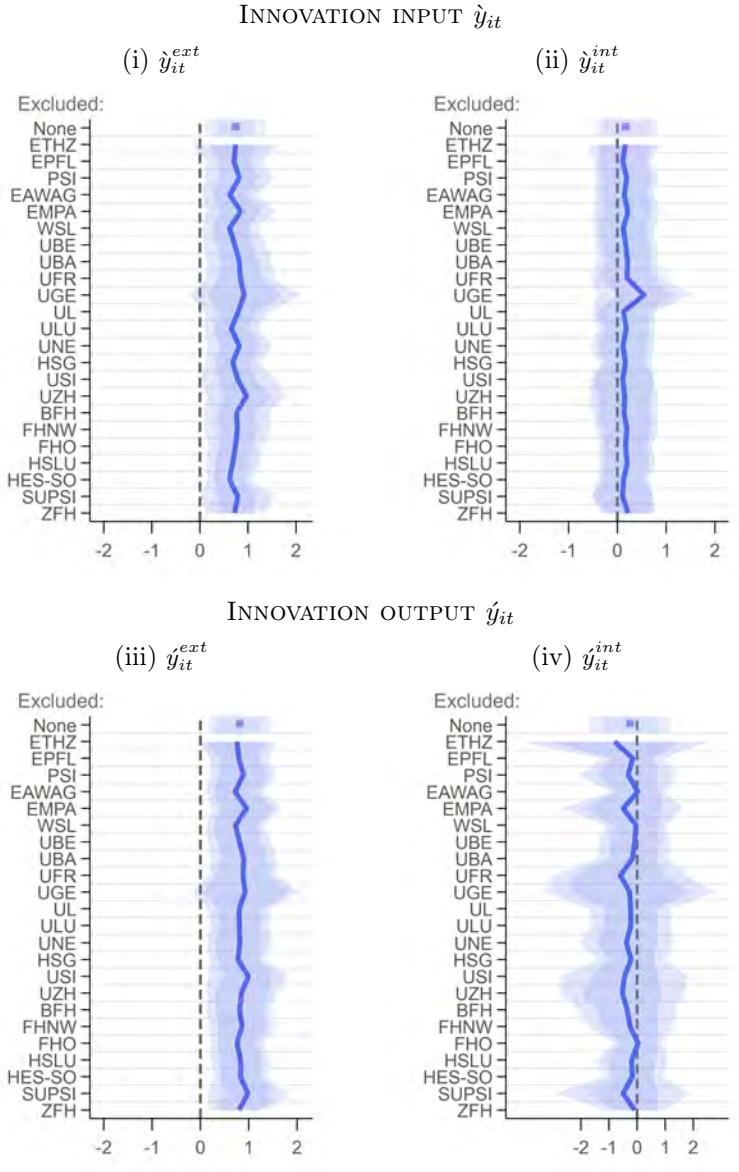
	SSIV			
	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$
x_{it}	0.159	-0.773	0.675	-0.354
	(0.340)	(1.008)	(0.362)	(0.959)
	[0.231]	[0.832]	[0.285]	[0.568]
w_{it-1}^{1}	✓	✓	✓	✓
w_{it-1}^{2}	✓	✓	✓	✓
w_{it-1}^{3}	✓	✓	✓	✓
w_{it-1}^{4}	✓	✓	✓	✓
e_{it}	✓	✓	✓	✓
μ_t	✓	✓	✓	✓
N	5044	1432	5044	2279
$N_{s_{nt}}$	50.97	49.41	50.97	49.82
N_{s_n}	17.64	16.80	17.64	17.16
F_{KP}	17.41	1.89	17.41	2.10
F_{AR}	0.43	1.93	5.60	0.55

Note: This table shows a modified version of table 4-3 using controls that account for network effects, i.e. w_{it-1}^{1}, w_{it-1}^{2}, w_{it-1}^{3}, and w_{it-1}^{4}, as well as the shift-share average of the natural logarithm of the size of the universities staff e_{nt} constructed as $e_{it} = \sum_n s_{itn} e_{nt}$. The innovation measures comprise indicator of internal R&D expenses, $\grave{y}_{it}^{ext}$, the natural logarithm of R&D expenses, $\grave{y}_{it}^{int}$, an indicator of recent product innovations, $\acute{y}_{it}^{ext}$, and the natural logarithm of sales from those product innovations, $\acute{y}_{it}^{int}$. The regression use the shift-share instrument with shocks g_{nt}^{shr} outlined in equation 6 and $\sigma = 3/4$. Following Borusyak et al. (2022), I report robust standard errors that come from heteroskedastic shock-level regressions of equation 5 and account for error clustering for firms with similar exposures noted by Adão et al. (2019) in parentheses. The standard errors in brackets come from heteroskedasticity robust firm-level regressions. Observations N are firm-year pairs and exclude those with controls and intensive margin outcomes in the top and bottom 5‰ to correct for outliers. Following the suggestion of Borusyak et al. (2022), I report the effective sample sizes $N_{s_{nt}} = 1/\sum_{n,t} s_{nt}^2$ and $N_{s_n} = 1/\sum_n s_n^2$ corresponding to reciprocal of the exposure concentration among shocks nt or universities n, respectively. F_{KP} is the first stage F from the Kleibergen and Paap (2006) rk test and F_{AR} the reduced form F of the Anderson and Rubin (1949) test.

A.IV Robustness

A.IV.i Leave-one-out

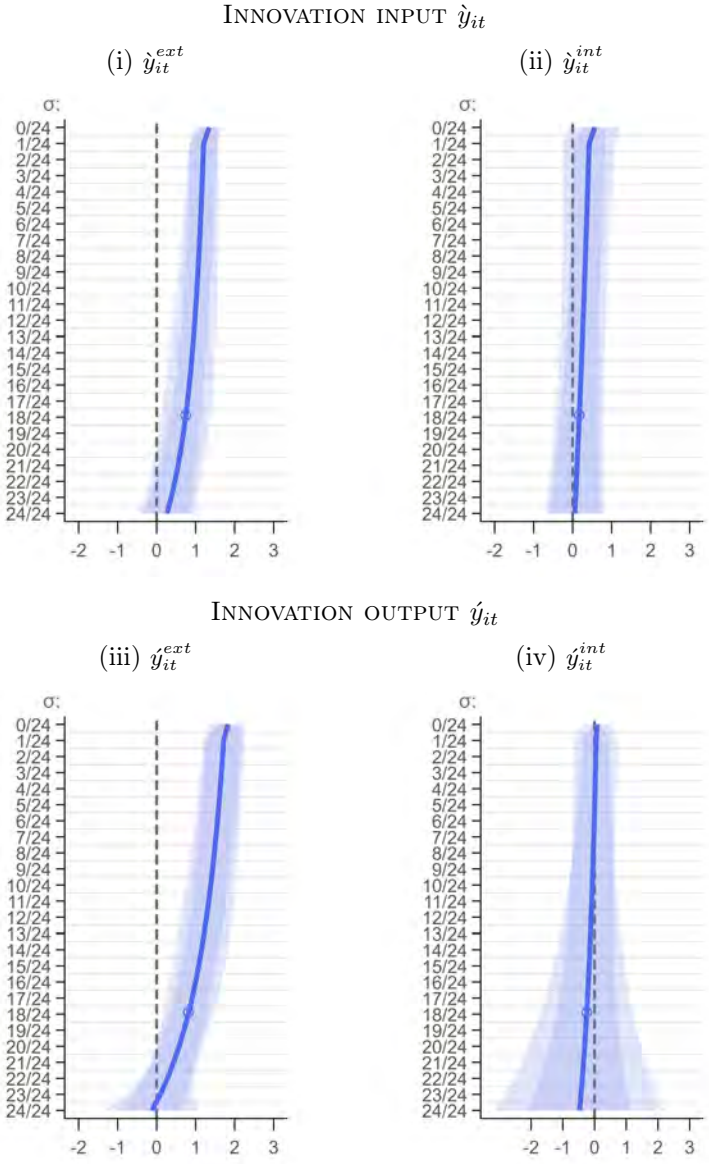
Figure A.VIII: Shift-share estimates with one university left out at a time



Note: This figure shows the gravity that each university exerts on the SSIV estimates reported in table 4-3. Subfigure i and ii show the results for the innovation inputs, namely the indicator of R&D expenses $\grave{y}_{it}^{ext}$ and the natural logarithm of the R&D expenses $\grave{y}_{it}^{int}$, while subfigure iii and iv show the results for the innovation output, namely the indicator of novel or improved products $\acute{y}_{it}^{ext}$ and the sales from those products $\acute{y}_{it}^{int}$. The top estimate of each subfigure labelled *None* refers to the instrument that includes all universities and coincides with the numbers reported in table 4-3. The estimates below come from instruments that drop the university mentioned on the left. The darker shaded area shows the confidence band associated with firm-level regression while the lighter shaded area stems from shock-level regressions. The significance level is 95% throughout.

A.IV.ii Alternative exposures

Figure A.IX: Shift-share estimates with different spatial exposure weights



Note: This figure shows the influence of the spatial exposure weight σ from equation 7 on the SSIV estimates reported in table 4-3. Subfigure i and ii show the results for the innovation inputs, namely the indicator of R&D expenses $\grave{y}_{it}^{ext}$ and the natural logarithm of the R&D expenses $\grave{y}_{it}^{int}$, while subfigure iii and iv show the results for the innovation output, namely the indicator of novel or improved products $\acute{y}_{it}^{ext}$ and the sales from those products $\acute{y}_{it}^{int}$. The void circle references a weight of $\sigma = 3/4$ as reported in table 4-3. The darker shaded area shows the confidence band associated with firm-level regression while the lighter shaded area stems from shock-level regressions. The significance level is 95% throughout.

A.IV.iii Alternative outcomes

Table A.XII: The effect of university knowledge transfers on firm innovation

	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\check{y}_{it}^{ext}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$
			Original		
x_{it}	0.144	0.089	0.088	0.148	0.103
	(0.027)	(0.108)	(0.021)	(0.033)	(0.768)
			Standardized		
x_{it}	0.145	0.028	0.122	0.139	0.011
	(0.028)	(0.034)	(0.029)	(0.031)	(0.086)
$\mathbf{w}_{it-1}$	✓	✓	✓	✓	✓
μ_i	✓	✓	✓	✓	✓
μ_t	✓	✓	✓	✓	✓
N	2263	487	2506	2548	485
R^2_{adj}	0.65	0.84	0.59	0.32	0.11

Note: This table provides a version of table 4-1 with alternative innovation measures y. It shows the estimates of β_{1y} using the two-way fixed effects (μ_i,μ_t) regressions with start-of-period controls $\mathbf{w}_{it-1}$ outlined in equation 2. The alternative measures for innovation inputs $\grave{y}_{it}$ include an indicator of R&D staff at the end of the last completed fiscal year, $\grave{y}_{it}^{ext}$, and the natural logarithm of the R&D staff at the end of the last completed fiscal year measured in full-time-equivalents, $\grave{y}_{it}^{int}$. The alternative measures for innovation outputs $\acute{y}_{it}$ include an indicator of successful process innovations in the last three fiscal year, $\acute{y}_{it}^{ext}$, and the cost reductions from those innovations in the last fiscal year measured in percentage points, $\acute{y}_{it}^{int}$. Additionally, $\check{y}_{it}$ measures the innovation intermediates via the presence of any patent applications in the last three fiscal years, $\check{y}_{it}^{ext}$. The upper panel uses unadjusted measures while the lower panel uses standardized outcome and treatment variables. The standard errors come from heteroskedasticity robust firm-level regressions. Observations N are firm-year pairs and exclude those with controls and intensive margin outcomes in the top and bottom 5‰ to correct for outliers.

A.IV.iv Sample split

Table A.XIII: The effect of university knowledge transfers on firm innovation

	TWFE				SSIV			
	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$	$\grave{y}_{it}^{ext}$	$\grave{y}_{it}^{int}$	$\acute{y}_{it}^{ext}$	$\acute{y}_{it}^{int}$
	Original							
x_{it}	0.136	0.160	0.057	0.088	0.704	-0.296	0.733	0.087
					(0.314)	(1.263)	(0.339)	(1.660)
	[0.033]	[0.119]	[0.031]	[0.097]	[0.218]	[1.406]	[0.249]	[1.094]
	Standardized							
x_{it}	0.131	0.040	0.059	0.026	0.677	-0.073	0.771	0.025
					(0.301)	(0.311)	(0.357)	(0.473)
	[0.031]	[0.030]	[0.032]	[0.029]	[0.210]	[0.346]	[0.262]	[0.311]
$\mathbf{w}_{it-1}$	✓	✓	✓	✓	✓	✓	✓	✓
μ_i	✓	✓	✓	✓				
μ_t	✓	✓	✓	✓	✓	✓	✓	✓
N	1743	504	1743	818	3362	1309	3362	2018
$N_{s_{nt}}$					51.27	49.75	51.27	50.21
N_{s_n}					17.70	16.86	17.70	17.24
F_{KP}					23.16	5.50	23.16	4.85
F_{AR}					10.33	0.05	9.22	0.01

Note: This table shows the standardized estimates of β_{1y} from 2 and 4a or 5a for the innovation outcomes y *excluding firms that never pursued innovations in the past.* $\grave{y}_{it}^{ext}$ is an indicator of internal R&D expenses, $\grave{y}_{it}^{int}$ is the natural logarithm of R&D expenses, $\acute{y}_{it}^{ext}$ is an indicator of recent product innovations, and $\acute{y}_{it}^{int}$ is the natural logarithm of sales from those product innovations. The first 4 columns (TWFE) correspond to the two-way fixed effects (μ_i,μ_t) regressions with start-of-period controls $\mathbf{w}_{it-1}$ outlined in equation 2. The latter 4 columns (SSIV) correspond to the instrumental variable approach outlined in equation 4 and 5 using the shift-share instrument with shocks g_{nt}^{shr} outlined in equation 6 and $\sigma = 3/4$. Following Borusyak et al. (2022), I report robust standard errors that come from heteroskedastic shock-level regressions of equation 5 and account for error clustering for firms with similar exposures noted by Adão et al. (2019) in parentheses. The standard errors in brackets come from heteroskedasticity robust firm-level regressions. Observations N are firm-year pairs and exclude those with controls and intensive margin outcomes in the top and bottom 5‰ to correct for outliers. Following the suggestion of Borusyak et al. (2022), I report the effective sample sizes $N_{s_{nt}} = 1/\sum_{n,t} s_{nt}^2$ and $N_{s_n} = 1/\sum_n s_n^2$ corresponding to reciprocal of the exposure concentration among shocks nt or universities n, respectively. F_{KP} is the first stage F from the Kleibergen and Paap (2006) rk test and F_{AR} the reduced form F of the Anderson and Rubin (1949) test.